Spatio-temporal patterns and pedestrian simulation

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**NANYANG
TECHNOLOGICAL
UNIVERSITY**

**SPATIO-TEMPORAL PATTERNS
AND PEDESTRIAN SIMULATION**

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2014**

SPATIO-TEMPORAL PATTERNS AND PEDESTRIAN SIMULATION

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Summary

Pedestrian behavior is an interesting social phenomenon. Understanding such crowd behavior has many important applications in computer animation, digital entertainment, civil planning, military training, etc. Despite significant research and development efforts, it still remains a challenging task. Thorough understanding of pedestrian behaviors requires true multiple disciplinary scientific research. With the fast development of computational technologies, modeling and simulation has become an important approach to understanding crowd dynamics. This thesis continues this trend and aims to model human-like steering behaviors of pedestrians. While simulation is an attractive approach to understanding crowd dynamics, evaluation, in particular, validation of pedestrian models is very much an open research question. This thesis also contributes to this area by the development and application of a three-stage validation method.

The thesis starts with a comprehensive review of both pedestrian studies from social and psychological research, and existing modeling and simulation techniques. This work provides a theoretical basis to understand pedestrians' navigational behaviors and thus helps support a computational model for realistic simulation. Based on existing pedestrian studies and observations on pedestrians' steering behaviors in real life situations, a tri-layered modeling structure of their navigational behavior is proposed, which focuses on modeling the middle layer between the traditional path planning and locomotion layers. This middle layer characterizes some commonly observed steering behaviors as steering strategies. A pattern-based approach is used to mimic the cognitive process of pedestrians. This approach describes: a perception process which pedestrians use to assess the situation through Spatio-Temporal Pattern (STP); a method for choosing corresponding steering strategies; and finally a way to execute these strategies. A small number of commonly observed steering strategies are used to produce complex steering behaviors. Decisions on the selection, scheduling and execution of steering strategies in a given situation are based on the matching result between the currently perceived concrete STP and the prototypical STPs stored

in an agent’s experience base. The STP representation and a hierarchical matching mechanism have also been proposed to formulate the experience of a pedestrian and to imitate the cognitive process involved in their steering process.

Validation of a computational model is a challenging task in pedestrian simulation, and it is still an emerging research topic in this area. To bridge this gap and to evaluate the proposed model in a systematic manner, a three-stage validation method is proposed through: (1) comparison studies against controlled field experiments, (2) model comparisons in standard test cases adopted from the literature, and (3) a sensitivity analysis of the model parameters. Such a validation methodology is based on a comprehensive review of evaluation techniques used in crowd simulation. Existing validation types and techniques are first categorized along different dimensions. A sequence of validation processes for different validation types is then conducted in three stages. The results are analyzed and demonstrate that the proposed model (1) is capable of generating quantitatively more similar simulation results to the experimental data than other comparing models in selected scenarios; (2) presents various crowd phenomena as reported in the literature, reproduces the collective efficiency and various crowd dynamics under different complex scenarios and (3) is robust to generate simulation results according to different key parameter values. Such results suggest that the proposed approach fulfills the objectives of generating realistic steering behavior of pedestrians in various situations.

In summary, the contributions of this thesis primarily fall into three parts. First, a tri-layer motion modeling structure to simulate the navigational behaviors of pedestrians has been proposed. In addition to the traditional two layered motion modeling system through path planning and locomotion control, a strategic steering behavioral layer in the middle of the traditional two has been explored in the thesis. Secondly, a novel pattern-based approach is proposed to model pedestrians steering behaviors realistically at this layer. A pattern-description method is proposed to describe and specify the novel spatio-temporal patterns, and a hierarchical pattern-matching process is developed to mimic the decision-making process. Thirdly, a comprehensive review of the model validation methods for crowd simulation has been discussed. The result is a novel three-stage validation methodology, which in turn is applied to the proposed model and demonstrates the model is capable of producing realistic crowd dynamics.

Acronyms

ABM agent-based modeling.

MRI Magnetic Resonance Imaging.

NDM Naturalistic Decision-making.

PBS Pattern-Based Steering.

PDM Pattern Description Method.

RPD Recognition-Primed Decision-making.

SC spatial constraint.

SME Subject Matter Experts.

STP Spatio-Temporal Pattern.

Glossary

actual velocity (V_a) actual velocity.

aggregated similarity (F) the aggregated similarity between two slices as a vector of similarities over all the ranges specified in the slices.

attention column (C) a distinctive spatial area along a direction that is specified by two consecutive vision radials.

attention range (R) the distance from the agent to form different attention zones.

attention section a mutually separated spatial area through the intersection of different attention ranges and vision radials.

attention zone the the specific spatial area within a attention range, where specific cognitive weight (attention) is allocated.

average acceleration (a) average acceleration of all agents.

average angular acceleration (α) average angular acceleration of all agents.

average inconvenience ($\bar{I}$) average inconvenience per simulation frame.

biomechanical energy (E) biomechanical energy spent in conducting certain behaviors.

biomechanical energy by steering (E_s) biomechanical energy caused by steering behaviors of agents.

cognitive weight (ω) a measure between 0 and 1 to indicate the likelihood of visual attention at a specific section along both spatial and temporal dimensions in an STP.

commitment level (δ) a model parameter defined to mimic the personal traits of an individual in her preference of the partial matching level to trigger a steering strategy.

completion time (T) time that all agents take to complete a simulation run in terms of number of frames.

concrete STP ($\mathbb{A}$) a currently formed STP through sensing and perception from the situation.

corresponding range (f') a range in the slice of a concrete STP that have the same relative location of the original range to the central column of the first row.

deviation distance (d_s) a deviation distance of the following position behind the target agent during the execution process of the follow steering strategy.

difference of local slope (ΔLC) the difference between the local slope of two participants at a specific time.

direction change ($\sum \Delta|A|$) total direction (angle) change made by all agents in a simulation.

distance from central column (l) the distance between the center of a range and the nearest central attention column (in case there are even number of attention columns). It is measured in the number of attention columns.

dynamic obstacle (D) an obstacle that may change its position during the moving process. In this context of this study, it normally refers to other agents that are perceived by an agent.

existence operator ($\rightarrow$) an operator defined in the Pattern Description Method to indicate the existence of certain spatial patterns at a particular slice.

experience instance (E) a tuple consisting of a prototypical STP, a steering strategy and the procedural execution process of the steering strategy to mimic the experience of a pedestrian.

follow steering strategy an active cognitive process and the subsequent sequence of actions, where an individual decides consciously to remain behind someone or some group moving in the same general direction.

gap distance (d_f) a distance to maintain during the execution process of the follow steering strategy.

horizontal direction line a line indicating the main moving direction of agents in the environment, which is parallel to the x-axis of the coordinate system.

horizontal spatial span (w) the perceived size of an element in front of an agent. It is measured through the number of attention columns that the element occupies in the attention system of an agent.

inconvenience (I) a measure of cognitive effort made by agents in making new decisions during navigation.

instinctive reaction behaviors that help resolve an imminent collision at the last moment.

local slope (lc) the instantaneous change in moving directions between a participant's consecutive steps.

main motion axis an axis that is parallel to the main moving direction of pedestrians in a scenario.

maximum deviation distance (D) maximum deviation from the horizontal direction line.

model evaluation a systematic acquisition and assessment of information to provide useful feedback about an object (simulation model).

model validation substantiation that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of a model.

negation operator ($\neg$) an operator defined in the Pattern Description Method to negate the value of a section or a range of sections.

normalized match score (γ_{norm}) the normalized similarity level between two slices. It is obtained through normalizing the overall match score of two comparing slices over the sum of cognitive weights for all the ranges in the slices.

overall attention area the whole spatial area, within which the sensed spatial information is relevant to form the concrete STP.

overall match score (γ) the measure to quantify the degree of matching between two comparing slices. It is calculated as a weighted sum of the aggregated similarity for a slice.

overtake steering strategy an active cognitive process where an individual decides to catch up and then move ahead of people in front of them in order to achieve certain goals (e.g., to maintain higher speed while avoiding collisions with people who are moving slower in front).

persistence operator ($\}$) an operator defined in the Pattern Description Method to indicate the persistence of certain spatial patterns over several consecutive slices.

personal space factor (ρ) a ratio of the radius of an agent to model the preserved personal space around a pedestrian during the social interaction (e.g. navigation process).

preferred velocity (V_p) preferred velocity.

preferred velocity to goal (V_g) velocity towards the agent's immediate subgoal.

procedural execution (ac) a typical sequence of actions to execute a steering strategy.

prototypical STP ($\mathbb{B}$) a form of STP that can match a number of different concrete STPs and has the same structure as a standard STP, but with some spatial and temporal characteristic not defined.

range (f) a consecutive number of sections in a slice of an STP, where certain spatial configuration is checked.

range operator ($[]$) an operator defined in the Pattern Description Method to specify a range of columns in a row of a slice.

reserved distance (d_d) a deviation distance reserved during the catch-up process between the agent and the target in the execution process of the overtake steering strategy.

section a particular cell of a slice corresponding to the spatial area as visually sensed by an agent.

separation distance (d) the distance between two participants.

side-avoid steering strategy an active cognitive process, where an individual perceives an individual or group of people coming towards her that may result in potential collision and tries to proactively avoid them.

slice (p) a visual representation of the perceived spatial patterns for a particular time frame.

speed (s) the speed of a participant.

speed change ($\sum \Delta|V|$) total speed change made by all agents in a simulation.

static obstacle (O) an obstacle that does not change its position during the moving process. In this context of this study, it normally refers to the environmental constraints observed by an agent.

steering strategy (S) seemingly planned behaviors adopted by pedestrians frequently and repeatedly to avoid collisions with tentative cognitive control and coordination.

steering velocity to approach lane (V_s) velocity driving the agent approaching the lane behind the target in the execution process of the follow steering strategy.

steering velocity to deviate away from the target (V_d) a velocity to deviate away from the target to approach to the space beside the target during the catching up process of the overtake steering strategy.

steering velocity to increase the speed (V_i) a velocity to increase the agent's speed in order to catch up with the target agent in the execution process of the overtake steering strategy.

steering velocity to reduce speed (V_r) velocity to reduce the agent's speed in order to match with the target agent in the execution process of the follow steering strategy, or to resume its original speed after the overtaking process.

Spatio-Temporal Pattern (STP) a pedestrian's perceived local spatial configuration (including other nearby pedestrians or obstacles in the situation) and how that changes over time.

symmetric range (f'') a range in the slice of a concrete STP that are mirror symmetric with a corresponding range about the central attention column.

threshold of match score ($\gamma_{threshold}$) a threshold value that defines the degree of freedom in the uncertain handling for slice matching.

time horizon (τ) a model parameter of the RVO2 model to specify the period of time in advance in the calculation of the available velocity to avoid collisions.

trajectory length (L) trajectory length, which is measured as the sum of distances at each unit time interval (0.05 s in experiments and 1 time step in simulations).

value sequence (X) a sequence of values for a range of sections in an STP to represent the spatial configuration of the range.

vertical distance (d) the projected distance from the observing agent to an observed agent along the preferred velocity of the observing agent towards its goal. It is measured through the number of attention columns that the element occupies in the attention system of an agent.

vision angle a term to indicate how wide a pedestrian can visually sense the environment. It is the angle between the two vision boundaries.

vision boundary a term to define the limit of peripheral vision.

vision center the central sight line of a pedestrian, which in most cases aligns with the moving direction pointing from the current position to the destination.

vision radial radials that are used to model the sight line of a pedestrian along a specific direction.

vision range a term to indicate how far in front of a pedestrian that she visually senses and responds to the visual information.

Chapter 1

Introduction

1.1 Background

Human crowd behavior is an interesting social phenomenon. It is fascinating to observe that efficient and relatively ordered social behaviors can emerge from sophisticated interactions of highly heterogeneous and dynamic individuals. The simulation of human crowd behaviors involves multi-disciplinary research in different fields such as social science, psychology, biology and computer science. Due to the advancement of computer technologies, modeling and simulation has fast become one of the most promising, yet challenging approaches for replicating and analyzing crowd behaviors.

Among crowd behavior studies, *navigational behaviors* of crowds in urbanized situations (i.e., pedestrian crowds) have drawn special research attention [6, 15, 19, 59, 70, 135] for its fundamental importance in crowd behavior research and its tight bond with almost everybody in real life situations. *Pedestrian simulation* is a process of simulating navigational behaviors of pedestrians in different environments under various situations. It has been widely applied in not only the entertainment industry such as games and movies [158, 169, 206, 218], but also in more serious research fields such as military and urbanized scenarios [116, 223, 228, 233] to study crowd flow [71, 85, 177, 212] and pedestrian movement patterns [33, 74], and to evaluate safety [62, 98], comfort [193, 245] and efficiency of different structures and environments [69, 187, 191]. In many of these applications, realistic simulation results generated by a model are crucial for the model users to draw accurate and reliable conclusions [23, 106]. As a result, building models capable of generating realistic navigational behaviors of pedestrians has become an emerging research topic [160, 206].

The navigational behaviors of a pedestrian crowd are complex and can be investigated and modeled from different aspects. May [129] proposed that crowd simulation can be divided into macroscopic and microscopic levels. Macroscopic level simulation

attempts to address the crowd movement from the aggregate level. For example, it describes a crowd with fluid-like properties instead of identifying individuals of the crowd. Partial differential equations [1, 72, 85, 137] are commonly used to describe crowd properties such as the fundamental diagram (i.e., the relationship between the crowd density and the flow speed [49, 185]) in macroscopic models. On the other hand, microscopic level simulation focuses on modeling individual constituents of the crowd and their interactions, from which the crowd behaviors emerge. When compared with the macroscopic approaches, microscopic level simulations generally provide more simulation details on the behaviors of individuals in the crowd. While macroscopic level of crowd behaviors have been studied extensively by researchers to understand the overall crowd dynamics [201] and their impact on applications such as egress and evacuations [17, 72], research in the microscopic level of crowd behaviors has been focused on exploring the dynamic individual behaviors and their complex interactions to meet the demands of various applications [9, 158, 204, 207]. Microscopic simulation not only reveals the emerging crowd dynamics, but also provides insights on why a certain crowd feature is exhibited under specific situations. Therefore, a microscopic model is an important tool to study pedestrians' navigational behaviors.

For microscopic simulation of pedestrians' navigational behaviors, agent-based modeling (ABM) is one of the most common approaches [127, 143, 157, 158, 172, 186, 188]. In ABM, a system is modeled as a collection of autonomous decision-making entities called agents. Each agent has specific properties and it assesses its environment, makes decisions and executes various actions individually through a cognitive process. Complex emergent phenomena arise from the interactions of simple behaviors among many agents, and it provides a natural description of a system [20]. A key issue in ABM of crowds is modeling the cognitive process, especially the decision-making processes of individual agents. Although various cognitive [115, 119] and decision-making frameworks [5, 66, 156, 240] have been proposed, these methods focus more on the mathematical formulation rather than the imitation of human-like mechanisms. Thus, models built based on such frameworks are commonly referred to as *rational* decision-making models, which aim to generate *optimized* outputs given a set of conditions [165]. On the other hand, research has been carried out to investigate the Naturalistic Decision-making (NDM) mechanism that is possibly involved in real-life human activities such as pedestrians' navigation. *Visual perception* [53, 172] and *experience* [77, 197] have been suggested as important components in human's cognitive

process through these studies. To model the pedestrians' navigational behaviors realistically as a result of the naturalistic cognitive process, it is thus important to adopt such concepts in the design and development of the system.

According to Zeigler [241], there are three main functions of ABM: to describe (replicate), to predict, or to explore a real system. Despite the effort in trying to explore the naturalistic cognitive process based on various tangible (e.g. spatial constraints in the environment) and intangible factors (e.g. various personal traits of an individual), there is still no consensus on the actual pedestrians' cognitive process during their navigation. Therefore, in pedestrian simulation, ABM is generally applied to *replicate* the navigational behaviors of pedestrians and to potentially *explore* [44] the cognitive mechanisms underneath. The design of a realistic simulation model can start with the understanding of the pedestrian navigational behaviors through observation and existing pedestrian studies, which could in turn, provide a set of hypothesis of pedestrians' cognitive mechanisms to form the theoretical basis of a computational model. The simulation results can then be tested to evaluate whether the model captures some insights of the real world system by checking whether it can replicate similar pedestrians navigational behaviors realistically.

Evaluation, in particular, the *validation* of a simulation model is an important issue in ABM [10, 180]. In order to make use of a model in an intended way, model validation is critical. In the context of pedestrian simulation, model validation determines whether an agent is an accurate representation of a pedestrian, and whether the simulated motion of agents replicate similar navigational behaviors of pedestrians in corresponding situations in real life. Model validation is still one of the most challenging research topics in human behavioral simulation [57] and it has been lacking in pedestrian simulation [12, 105]. There are different types of validity of a model and different validation methods to address each of them. Previous works [148, 159, 196, 201] have made good attempts at validating a microscopic pedestrian or crowd simulation model from certain aspects (e.g., facial validity, functional validity); however, these have been done in an ad-hoc manner. A common protocol on systematic and comprehensive validation of such models is yet to be achieved.

In summary, great progress has been made in recent years in pedestrian simulation given its wide applications. However, there still does not exist a standard accepted model of pedestrian motion that is capable of generating realistic steering behaviors under different situations. Despite the effort given to validation and its importance in ABM, the methodology for validating such models is still an open research question. This thesis tries to contribute to this emerging research area.

1.2 Motivation

In real world situations, various cognitive and navigational activities are involved for pedestrians to reach their destinations in a complex and dynamic environment with static obstacles and moving objects. Although humans are able to move smoothly, almost effortlessly even in crowded places, it is still a challenging task for computer programs to imitate such behaviors realistically. From a computational modeling point of view, complex navigational behaviors have been typically modeled through two levels of activities of an agent: *path planning* and *locomotion*. Path planning can be considered to be the higher-level cognitive activities that generate a global path directing the agent from its current position to the goal. It typically considers the static aspects of the environment, such as walls and doorways in the relatively long term in both spatial and temporal domains. Locomotion is a lower-level cognitive activity to move the agent along the path while avoiding collisions. This bi-level methodology is effective in some applications, but lacking when it comes to the reflection of the naturalistic cognitive process of pedestrians and the generation of realistic navigational behaviors.

Existing methods relying on mathematical mechanisms such as [19, 69, 219, 221] control an agent's motion, for each simulation step, at the *locomotion* level directly for collision avoidance. They try to achieve an optimized (i.e., in terms of the minimum collision rate) motion for each agent in a computationally efficient manner. However, these approaches have some major disadvantages:

- **Lacking real system reference:** These approaches formulate the problem purely from a mathematical or physical point of view for collision avoidance. However, the cognitive mechanism of a pedestrian might be totally different from a mathematical collision-avoidance algorithm. Thus, such methods may not be intuitive for the user to understand and to correlate the model with the behaviors of pedestrians in the real world.
- **Homogeneous individuals:** Existing approaches generally provide a single optimal solution for all the agents to act in either a completely cooperative (i.e., RVO2) or competitive (i.e., Social Force) manner. Individual characteristics due to some intangible factors of pedestrians is difficult to incorporate into such models.

- **Calibration difficulties:** The calibration of such models is difficult as a single model tries to capture the complete range of crowd behaviors through sophisticated mathematical ruling functions. These functions need to be extended as new observations in crowd behaviors are made, which in turn creates challenges for the calibration of the model [135].
- **Artificially optimized behaviors:** The individuals are operating within the local constraints enforced by predefined global optimum (e.g. being collision free). Optimization under such constraints generates strange synchronous phenomena in certain conditions and results in unnatural oscillations known as the “reciprocal dance” problem [47], often ending in a deadlock situation [198].

Instead of frequently adjusting their motion at every step, pedestrians are often observed to avoid collisions smoothly. A planning-like strategic steering mechanism seems to be involved in this process. We refer to such strategic cognitive activities involved at the level between the traditional two as the *local path determination*. The central assumption of this thesis is that the navigational behaviors of pedestrians can be modeled realistically through hierarchical motions in three layers of *path planning*, *local path determination* and *locomotion*. The inter-relationship between the three layers is illustrated in Figure 1.1.

Figure 1.1: Hierarchical modeling problem.

The goal position WP_n is first received by the *path planning* layer, which then uses a route finding algorithm such as A-star [65] in the path planning function $PP()$ to find a set of way-points that will lead the agent from the current position WP_0 to the goal position through the environment. The set of obstacles O is considered in the function. The list of way-points $\{WP_0, WP_i, \dots, WP_n\}$ forms the global path from the current position to the goal. The algorithms are generally well-studied at this layer of motion and thus it is not the focus of this thesis. As the output, this layer returns the next way-point WP_i that the agent has to reach and passes it to the next layer of navigation.

The *local path determination* $LP()$ differs from the higher layer in that it takes into consideration both the set of static and dynamic obstacles O and A (i.e. other agents), to determine a local path from the current location to the next way-point, in which the agent potentially avoid collisions. The research focus described in this thesis is on this layer of navigational behaviors. As the output, this layer calculates a preferred velocity $\vec{V}_{preferred}$ to instruct the agent executing a certain selected steering strategy.

Theoretically, $\vec{V}_{preferred}$ does not guarantee collision avoidance because the steering strategies are selected based on the perception of the dynamic situation, including the predicted status of other agents, who themselves use such dynamic planning. It is inevitable that collisions may happen if agents purely follows their preferred velocities. Hence, some Motion Adjustment mechanisms $MA()$ at the *locomotion* level are needed, when necessary, to avoid physical collisions. There are several popular collision avoidance algorithms such as Reciprocal Velocity Obstacles (RVO) [219, 221] and Social Force method [69]. These algorithms take a preferred velocity $\vec{V}_{preferred}$ and a set of obstacles (both static and dynamic) A and O as the input and output an actual velocity $\vec{V}_{actual}$ of the agent to ensure collision free motion. The major difference between this layer and the previous layer is that it has some noticeable adjustment on the motion of an agent only when a collision is imminent, because the preferred velocity fails to avoid collisions.

Such a tri-layer motion modeling structure provides several benefits to solve the problems of the previous bi-layer models. In particular, research focus on the local path determination layer could help address various research issues such as how to model the strategic steering behaviors of agents in order to imitate pedestrians' navigational behaviors realistically. At this layer, pedestrians deliberately plan their maneuver to minimize the chance of collisions, while moving from one point to another along the path. The planned maneuver affects its motion in a relatively short

period of time (i.e. a few second) and is referred as a set of *steering strategies* in this thesis. Such strategic steering behaviors do not necessarily reflect any *optimized* mechanism to guarantee the avoidance of collisions. We believe this could be a more natural way of describing and modeling pedestrians' navigational behaviors. Firstly, neuro-cognitive studies [29, 56] have suggested that complex decisions are not necessarily involved in most situations during pedestrians' navigation. Instead, they rely on simple steering strategies corresponding to different situations that they are familiar with. Such association of the situation and the corresponding steering strategy naturally forms parts of the *experience* in their cognitive process. Secondly, collision-avoidance is naturally a non-optimized problem in pedestrians' navigation. Collisions do occur among pedestrians from time to time under many situations in real life, we also note that children are more likely to collide with others in a crowd than adults. These observations raise many important research questions; for example, what factors cause such variation in navigational behaviors and how pedestrians react to different situations in terms of different steering strategies. Research on local path determination can help address these research issues.

1.3 Objectives and Contributions

The aim of the work presented in this thesis is to create an agent-based simulation model that is capable of generating natural and realistic navigational behaviors as of pedestrians in real life scenarios. To model the strategic steering behaviors realistically, we first review the relevant pedestrian studies that describe and explain certain aspects of pedestrians' navigational behaviors. Such studies will form the theoretical basis for the tentative simulation model. As discussed, the cognitive process of pedestrians involves the use of their experience and familiarity to certain situations. To model such a cognitive process, we adopt a novel *pattern-based* approach. At the structural level, the pattern-based approach reflects the NDM mechanism, which emphasizes on the role of experience in their decision-making process. In addition, the pattern-based approach takes into account various tangible and intangible factors that influence pedestrians' choice of steering strategies in an effective manner by embedding them into the representation of the patterns. Such a pattern-based approach provides several advantages to solve the problems of the existing approaches.

Model validation is an important, yet challenging research task in pedestrian simulation. Real data and meaningful metrics, and appropriate validation techniques are

critical for a meaningful validation process of such a model. To propose an appropriate validation method, different types of validation from the previous work are first reviewed and categorized in different dimensions. A sequence of validation process for different validation types is then conducted. The results will be analyzed and discussed to validate the proposed model.

The contributions of this thesis primarily fall into three parts. Firstly, we have proposed a tri-layer motion modeling structure to simulate the navigational behaviors of pedestrians. The focus of this thesis is on the *local path determination* layer, somewhere between *path planning* and *locomotion*. Secondly, a novel pattern-based approach is proposed to model pedestrians' steering behaviors realistically at this *local path determination* layer. A pattern-description method is proposed to describe and specify the novel spatio-temporal patterns, and a hierarchical pattern-matching process is developed to mimic the decision-making process. Thirdly, a comprehensive review of the model validation methods, in particular, for crowd simulation, has been discussed. The proposed model has been validated through a three-stage process, including real world experiments, model comparison under standard test scenarios and sensitivity analysis. This validation approach is fairly general and can be applied to other crowd simulation systems.

1.4 Organization of the Thesis

The rest of this thesis is organized as follows:

- Chapter 2 reviews the existing work mainly from two perspectives. First, pedestrian studies help us understand pedestrian behaviors from the social, psychological and ergonomic perspectives. Secondly, the existing simulation models on pedestrian behaviors provide an overview of the current approaches with their pros and cons and thus can be used to direct this research to overcome the disadvantages of existing approaches.
- Chapter 3 describes the theoretical basis for the pattern-based approach. Several assumptions to describe and explain pedestrians' navigational behaviors are first proposed based on the literature reviewed. Based on these assumptions, the tri-layered modeling structure for motion of pedestrians is discussed in detail. The cognitive process of perceive-decide-act is also discussed.

- Chapter 4 describes the concept of Spatio-Temporal Patterns (STP) used in this thesis. A pattern description method is then proposed for an STP description and specification.
- Chapter 5 depicts the pattern-based steering model for the strategic steering behavioral modeling of pedestrians. The key components in the perceive-decide-act cognitive process are discussed under the pattern-based approach.
- Chapter 6 separately discusses the challenges in validating microscopic pedestrian simulation models, reviews the existing methods used to validate crowd simulation models and proposes a three-stage validation methods for the pattern-based steering model.
- Chapter 7 discusses the validation process used in validating the proposed model in detail. To systematically validate the model, various techniques such as controlled field experiments, model alignment, and sensitivity analysis are applied in three stages. The validity and limitations of the model are demonstrated through this validation process.
- Chapter 8 concludes the work described in the thesis, summarizes the key contributions, and points out several research issues that are recommended for the future work.

Chapter 2

Literature Review

This chapter reviews relevant pedestrian studies and previous work on pedestrian and crowd simulation. We first examine various social and psychological pedestrian studies. We believe these studies can provide theoretical basis to understand pedestrians' navigational behaviors and thus to support a computational model for realistic simulation. Such studies can be used not only in the prototype design, but also in model calibration and validation processes. Different microscopic pedestrian simulation approaches and models are then reviewed and discussed. Major problems of existing models and the areas with potential to improve in the research are identified and shed light to our research focus presented in the thesis.

2.1 Pedestrian Studies

To simulate pedestrians realistically, we need to first study the pedestrian characteristics from studies of various fields. Macroscopic and microscopic pedestrian characteristics are reviewed accordingly in this section.

2.1.1 Macroscopic Pedestrian Characteristics

The macroscopic characteristics concern about a group or a crowd of pedestrians rather than individuals. Macroscopic characteristics can describe the overall motion features of a crowd from different aspects such as the flow rate [4, 140, 204], dominant direction [28], and the transitions of different motion patterns [108, 171] over time for the whole crowd. In this thesis, we are interested in those characteristics that can be potentially used in a microscopic pedestrian simulation model. For example, flow rate of a crowd in certain situations can be used to estimate the average speed of all the individuals in a crowd and thus applied in the model calibration process. In

particular, two fundamental characteristics of a traffic flow are the *average moving speed* and the *density* [68], which also applies to a pedestrian crowd [185, 225].

Average moving speed is an important parameter of pedestrian movement. Relevant studies may help calibrate the proposed model since individual pedestrian's speed will be influenced by the average moving speed of a crowd under certain situation (e.g., in a dense crowd). Several studies have attempted to describe the average moving speed of pedestrians depending on various factors such as the physical ability, social position (in a crowd) and the crowd density. Lovas [125] divided all of these factors into two groups as situational factors and personal factors, and assumed that the moving speed of a pedestrian crowd follows a logarithmic normal distribution. Henderson [72] measured the desired speeds of three crowd fluids, and found the speeds follow a Gaussian distribution with the mean value of 1.34 m/s and a standard deviation of 0.26 m/s . The variation can be even larger attributed to the sexual inhomogeneity. These empirical data will help calibrate the parameters of a computational model.

Density is another macroscopic characteristic relevant to pedestrian simulation, particularly in a complex scenario where a large number of people is involved. Local density surrounding a pedestrian can influence her navigational choices. Papacostas and Prevedouros [154] defined the pedestrian density formally as “the number of pedestrians within a unit area (ped/m^2)”. Helbing [68] observed that pedestrian density increases (i.e. interpersonal distances lessen) around particularly attractive places, and it decreases with growing velocity variance. Fruin [49] found the relationship between the space occupied per person and the average walking speed follows a saturation function. With this relation, pedestrians' speeds are believed to be limited according to the perceived local density. Fruin also pointed out that people are only able to walk at their characteristic speeds if the density is below $0.5\text{ ped}/\text{m}^2$. These studies have shown the relationship between the parameters that are likely considered in a model. Therefore, they can be used as guidelines during the implementation of a model. The fundamental diagram [49, 185] of density and the speed (or flow rate) of the crowd has been widely accepted as an important metric to quantitatively validate a crowd simulation model [59, 71, 184].

2.1.2 Microscopic Pedestrian Characteristics

Unlike macroscopic pedestrian characteristics, microscopic pedestrian characteristics are not clearly defined because individual pedestrians behave in a heterogeneous

way [204]. In general, any characteristic that describes the individual pedestrians in their movements and their interactions with the environment or other pedestrians could be considered as a microscopic pedestrian characteristic.

2.1.2.1 Speed and Direction

Speed and direction are the two important characteristics to describe an individual pedestrian's movements. Studies from ergonomics provide some empirical data that describes the space requirement and speed limit for pedestrians. The minimal physical space required by a normal person is 0.09 m^2 (based on the body width of 0.34 m) for a woman and 0.14 m^2 (based on the body width of 0.43 m) for a man. However, to feel comfortable, one needs to maintain a psychological distance [47]. Feurtey has given the table of psychological distance based on different intimacy level, which could explain the different space requirement for different pedestrians (e.g., less space between friends than strangers is required during navigation). He also suggested, based on the biological limits, that the normal walking speed of a pedestrian can range from 44 m/min to 122 m/min , which equals to $0.73 \sim 2.03\text{ m/s}$ as the unit m/s is used for walking speed of pedestrians in this thesis.

Pedestrians prefer to walk at an individual speed, which corresponds to their most comfortable walking speed in the situation with no time stress [68, 72]. Helbing [69] observed on purposeful pedestrians who steered for specific destinations. He pointed out that

“Pedestrians normally choose the shortest route to their next destination which has therefore the shape of a polygon. If alternative routes have the same length, a pedestrian prefers the one where he/she can go straight ahead as long as possible and change the direction as late as possible provided that the alternative route is not more attractive (due to less noise, more light, friendlier environment, less waiting time at traffic lights, etc.). A pedestrian feels a strong aversion to taking detours or moving opposite to the desired walking direction even if the direct way is crowded.”

These observations generally describe pedestrians' movements in terms of speed and direction, which can be used as the basic metrics to evaluate the simulation results of a model. In addition to these characteristics, studies of microscopic pedestrian characteristics were also conducted from different aspects, such as vision and attention, spatial perception, cognitive process and behavioral habits of a pedestrian. These studies are also important to understand and model the mechanisms that produce realistic pedestrians' behaviors.

2.1.2.2 Vision and Attention

When a pedestrian moves in an environment, the visual information she perceives is likely to affect her navigational behaviors. Various studies have been conducted to understand this information retrieval and filtering process, particularly for pedestrians.

Early research into pedestrians' navigational behaviors was conducted by Goffman [54]. He described how the environment is observed by a pedestrian through a mostly subconscious process in order to sidestep small obstructions, which he called *scanning*. His notation of scanning was also applicable to describe the interaction between pedestrians. According to this study, pedestrians check those who are within a small scanning area around them, but neglect the others. Such a scanning process is consistent with the later study of visual attention, which describes in more detail how different pieces of visual information are selected and filtered according to the salient features relevant to a specific task [39, 88].

Wolff [230] described the task of monitoring the environment as a way for people to evaluate the potential behaviors of others. He mentioned that avoidance action could be taken by pedestrians even at a far distance of $30m$ in a very low-density situation, as long as they sense each other. His study has extended Goffman's scanning area in a way that pedestrians will look further afield if no obstruction within the area catches their attention. The vision of a pedestrian, based on this study, thus can be thought of consisting of rasters of visionary radials, which help the pedestrian scan the environment. A visionary radial can extend far if it is not obstructed by obstacles along that direction. As a result, it seems that much information will be visually sensed through the scanning process. In such a case, there should be some mechanisms adopted by pedestrians to effectively filter out irrelevant information that may interfere with their steering choices.

Kahneman [94] studied the attention and effort of people during a task, and divided the looking behavior of a person into three possible types, of which, Rymill and Dodgson [175] pointed out that two are relevant in describing the vision and attention of pedestrians: *spontaneous looking* and *task-relevant looking*. Spontaneous looking occurs when a person views a scene without specific tasks in mind. It is the normal scanning for environment and no specific attention will be drawn. Task-relevant looking occurs when the person requires specific information to fulfill the need of a certain task. For example, the person that is being overtaken should be observed during the process to get accurate information to direct the steering behaviors of the

observer. Egeth and Yantis [39] tried to summarize the way people usually pay attention to objects. They pointed out that a number of factors such as the motion and the size of the object influence the attention capture. In contrast to Kahneman's work, their findings focus on attention, which is different from vision. When one is paying attention to something, it is not necessary to continuously look at it. Instead, accurate information may be obtained when the target is looked at later. During their navigational process, it is clear that attention plays an important role to enable pedestrians to select only the limited relevant information from massive information that can be sensed through the scanning process. The next research question is then, how pedestrians make use of the information retrieved and filtered through their vision and attention to direct their steering behaviors?

2.1.2.3 Spatial Perception

To select appropriate steering choices according to what is sensed from the environment, a pedestrian probably needs to form an understanding on the situation. Perception, according to [181], is the organization, identification and interpretation of sensory information in order to represent and understand the environment. In particular, pedestrians' spatial perceptions of the environment are believed to influence their navigational behaviors.

In cognitive psychology, Gibson's ecological theory of perception [53] has been widely applied. This theory is laden with subjective and objective knowledge and replaced them with a model in which the agent and its environment are conjoined by a set of *affordances*. Such affordances will be used to guide the agents action without reference to superior representational models of the environment. As summarized by Turner and Penn [215], Gibsons theory has provided the intermediate layer between the environment and people's decision and action. They referred to the environment as "the provider of possibilities rather than as a place to be rationalized". Although this layer was represented as "a set of affordances" in the original work, the author believes it can be viewed as pedestrians' spatial perception on the environment. The concept of affordance has been applied in pedestrians simulation recently by Kapadia etc [95, 96], who have proposed a general framework for local path planning and steering behaviors.

From the spatial-cognition perspective, there are also interesting findings related to pedestrians' spatial perception during navigation. Tversky etc [216] gave the term *three space* of spatial cognition to describe the way people interact with the space

around them. These three spaces are named space of navigation, space around the body and space of the body. They argued that

“Our knowledge of space is constructed out of the settings in the space rather than the space itself. Mental spaces are schematized, eliminating detail and simplifying features around a framework consisting of elements and the relations among them.”

This work explains why individual pedestrians’ spatial perception varies when viewing the same objective spatial settings from the cognitive level. In pedestrians’ cognitive process, the spatial perception helps them understand the environment in order to direct their steering behaviors.

From the behavioral-psychology point of view, the potential violation of space around the body and space of the body [216] imposes mental stress [114] on neighboring pedestrians. Sommer [200] has proposed a personal space model to estimate such mental stress. The concept of mental stress was extensively studied by Osaragi [152] and Sakuma [178], who later invented a two-stage personal space architecture to simulate the positional relationship between pedestrians.

Researchers have also conducted psychological experiments to prove the importance of spatial perception on people’s movement. Golledge [55, 56] proved that the perception on the configuration of the environment itself will influence the walking route choice through experiments conducted in a college campus. Hiller and Hanson [73] discovered the significant influence of spatial settings on microscopic movement from the perspective of space syntax.

More specifically, Daamen and Hoogendoorn [35] pointed out that there are two types of spatial usage as lateral and longitudinal usage in pedestrians’ movements. They created a formula for the relationship between the spatial usages and the moving speed. Such studies could provide empirical data to calibrate a model at the locomotive level. (e.g., lateral usage of the space guides the model to specify roughly how far away different entities should separate apart during their steering process to avoid collisions; while longitudinal usage of the space provides information on how far away an entity normally start to steer away from the potential colliding objects.)

2.1.2.4 Other Cognitive Components

In addition to the studies discussed above, pedestrians’ steering choices may be influenced by other cognitive components in the cognition process. In general, the

cognition process encompasses how people perceive information and transform it into mental states for decision making. In this section, some important concepts such as memory, attention range and prediction in psychological research will be reviewed.

Working memory (also referred as short-term memory or operant memory) is a theoretical construct within cognitive psychology that refers to the structures and processes used for temporarily storing and manipulating information [32, 45, 130]. It can store temporary information up to a few seconds and manipulate information to support instantaneous judgments. The capacity of working memory, according to Miller [130], is the “magical number seven”. While Cowan [32] proposed that working memory has a capacity of about four chunks in young adults and fewer in children and old adults. With only a limit of 7 ± 2 chunks of memory capacity, pedestrians need to handle a large amount of information by grouping similar information together. Ericsson and Kintsch [45] argued that human’s ability to handle information is extended by grouping information into chunks. They further noted that grouping can be made on different levels depending on the different levels of expertise. In other words, small chunks can be further grouped into larger chunks. Since most adult pedestrians are experienced walkers, grouping information on potential collisions is performed easily in daily life. Kids, however, may only be able to notice limited number of potential obstructions at a time. They also noticed that people are skillful in using memory for everyday tasks through not only the short-term memory, but also the long-term memory. People accomplish tasks by storing most of what they experienced in long-term memory, linking them through retrieval structures, and holding cues for the transfer of all information from the long-term memory to the working memory. From their work, we can summarize that experiences are usually stored in the long-term memory and the relevant information is retrieved through a experience matching process. Such studies suggest the decision-making process involved in daily tasks, such as the navigation of pedestrians.

Attention range is defined as the farthest range where an obstacle can be captured through a pedestrian’s working memory [178]. It relies on the pedestrian’s vision and attention as previously discussed. Attention range is not merely based on the spatial information but also the memory capacities. Because of the limited capacity of working memory, and also people’s tendency to handle closer potential threat first, attention range becomes smaller when the crowd density becomes higher.

Not only the status of obstacles that are currently within the attention range will be noticed, other objects that will potentially come into the attention range will also

be captured by the observing pedestrian through its mental prediction. Prediction is made based on the observed status of the obstacles in the attention range. Yarbus described the prediction in [238] as

“A person would be unable to detect the change in their peripheral vision, assumption can be made on the prediction process that it is merely based on the current status of other pedestrians that have been kept in the working memory.”

Although it is arguable that whether peripheral vision is sensitive to changes in the situation, prediction can be treated as a natural extension of the current status. Any significant changes detected in the peripheral vision will then interrupt the prediction.

Such an assumption seems to suggest that mental prediction is a linear deduction process along time, which may lead to inaccuracies in the decision-making process. For example, the position of one pedestrian may be far away from the position that another has predicted it to be. However, Rymill and Dodgson argued that “it should not be thought of as a problem, rather as an attempt to recreate, albeit simply, how the brain really works” [174]. These cognitive components and their functions in the cognitive processes of pedestrians have been briefly reviewed mainly from the psychological point of view. These works provide some theoretical support for the design and development of a model that mimics these cognitive processes.

2.1.2.5 Behavioral Habits

The internal cognitive process of a pedestrian dictates her behaviors. However, the heterogeneous behaviors of pedestrians can not be attributed solely to their cognitive processes, but also the instinctive behavioral habits of individual pedestrians. Behavioral habits have also been the focus in many pedestrian studies. Although most of these studies examined the walking behaviors on pavement where space is restricted, they can also be applied to an open area.

The social behavioral study in [64] suggests that human behaves differently in different context with specific behavioral characteristics. In the context of a pedestrian’s navigational behaviors, different steering behaviors can be observed in different scenarios. In experiments carried out by Wolff [230], pedestrians would start to avoid an oncoming collision when the other is around 1.5 m away in normal situations. However, with only a few people around, this would rise to a much longer distance (30 m). Goffman [54] agreed that people tend to avoid each other as early as possible in

order to maintain their ‘dignity’. Such studies suggest that *planning* to avoid collisions in advance is a necessary component in such behavior. Through planning, they can avoid close contact with each other as well as to minimize changes in movement directions. However, high density crowds offer less opportunity for early avoidance due to the unpredictability in the crowd. In this case, Wolff found that pedestrians will not detour and avoid contact by totally steering their path; instead, they react to the imminent collisions by performing what he called *step-and-slide* [230].

In terms of pedestrians’ steering behaviors to avoid collisions with others moving in the same direction, Wolff observed two kinds of behaviors, *follow* and *overtake*. When the *follow* behavior is in force, a pedestrian will not position herself directly behind the person in front, but will be slightly displaced so that she can see over his shoulder. According to Collett and Marsh [30], matching speed with pedestrians in front will reduce the effort required to avoid collisions. By following others, they may minimize their effort in collision avoidance. Macroscopic phenomena such as clustering can be generated from the follow behaviors of a crowd. The higher the crowd density, the more and larger clusters will be formed.

When the *overtake* behavior is activated, pedestrians will weave their way through the crowd by looking for opportunities either within their own lane, or along the interface with the opposing lane [230].. In order to travel faster, pedestrians will constantly look for empty spaces for overtaking. In a restricted area, opportunities may become rare when the density is high. In an open area, pedestrians may have to step off the pavement and walk on the road around the slow-moving cluster of people in front of them [230].

One of the characteristics that distinguishes these behaviors from other impromptu movements is that proactive *planning* is involved. We refer to such planning as *steering strategies* in our work. We believe that pedestrians do not make complex decisions in order to avoid collisions during steering at each step in their movement; instead, they often apply simple yet efficient steering strategies under different situations to plan their movement to avoid potential collisions in advance and thus achieve smooth movement.

Studies also investigate pedestrians’ steering behaviors to avoid pedestrians moving in the opposite directions. Dabbs and Stokes [36] studied how pedestrians grant space to each other to avoid potential collisions when they move towards each other. Willies [226] examined the factors that determine who moves first to resolve potential collisions between two oncoming pedestrians or groups. Such factors include power,

gallantry and maneuverability, of which, the latter two plays a more dominant role under normal situations. Although there is difference in terms of the priority to move first, a high degree of cooperation between pedestrians is an intrinsic part of pedestrian behaviors in general [230]. Such studies suggest that the interactions among pedestrians are not synchronized, but cooperation emerges at the aggregate level.

Concerning pedestrians' preferences on route choices, Garling and Garling [51] found that local route optimization is favored by most shoppers. Golledge [55] pointed out that a shortest-path route is not always chosen even when origin-destination pairs are well specified and the participant is well acquainted with the area, through the experiments they conducted. By using a virtual environment, Dalton [37] found that there is a tendency for pedestrians to reduce the total angle turned during their movement. He called this the *angular minimization rule*. These findings have shown various pedestrians' characteristics from the aspect of their behavioral habits.

To summarize, we have reviewed studies on various pedestrians' characteristics in this section. These characteristics facilitate our understanding of their behaviors from an aggregate level. Some of observations can be used in the design and calibration process of a computational model. The review on the microscopic characteristics from different perspectives provides more details on pedestrians. Starting from the basic motion features such as the dynamics of speed and direction in their movement, pedestrians' behaviors have been reviewed through the cognitive processes, where information is first captured from the environment through vision and attention, then to form the perception and how pedestrians behave accordingly to what they perceive in the cognitive process. Other relevant cognitive components and concepts such as the attention, memory and prediction have also been discussed. These studies provide important theoretical basis for the design of a simulation model.

2.2 Crowd and Pedestrian Simulation Models

Motivated by the diverse applications of crowd and pedestrian simulations, various simulation approaches and models have been proposed and developed. As this work focuses on the microscopic level to generate realistic steering behaviors of pedestrians, the review of the existing modeling approaches in this section focuses on the microscopic level of pedestrian behaviors.

According to the survey [15] on pedestrian movement modeling, the microscopic simulation of pedestrian movement faces three main challenges to achieve realistic simulation results. They are (1) the raw computer power limitation, (2) the lack of

proper mechanism for behavioral modeling from an individual’s perspective and (3) the complexity of the pedestrian behavior itself. Thanks to the fast development of computer technologies, the first challenge could be conquered. Agent-based modeling provides a promising mechanism to model each individual and its behaviors, thus to address the second challenge. The main difficulty in achieving a realistic simulation is the behavioral complexity itself.

There have been many attempts to simulate people’s navigational and steering behaviors ever since Reynolds’ pioneering work on *boids* [168]. Existing work can be broadly divided into four groups from different research perspectives.

2.2.1 Robotics-based Motion Planning

Collision avoidance is an important research area in the context of navigational behavioral modeling. There is a large body of existing work, aimed at either robotics navigation (e.g., [48, 52, 90, 192]) or crowd simulation (e.g., [122, 203, 219]). Such motion control and motion planning [78, 220, 236] methods generally consist of four steps in calculating a velocity at each step that leads the robot or virtual human to move towards its goal, while avoiding collisions. First, a valid velocity set is to be formed. Kinematic constraints often affect the definition of such a set. Next, a cost function is proposed to evaluate a velocity, which may combine different factors describing the situation and the possible consequence of a potential velocity (e.g., whether one will collide with others if move in a certain velocity in the next step; whether one keeps consistency in her speed with a chose velocity). In the third step, sample velocities from the velocity set are evaluated based on the cost functions defined. Eventually, a velocity with the optimal cost among those sample velocities is chosen to be assign to the object and to direct its movement.

These works tried to generate a collision-free motion for all agents in the simulation environment. A representative work is the *Reciprocal Velocity Obstacle (RVO)* model [220] and its variants (e.g., RVO2) [198, 221, 222]. It generally provides a single optimal (i.e., collision-free, and with minimal velocity change) solution for all the simulated entities in general situations. However, we argue that humans are non-optimal in their movement. Collisions do occur in some real world situations. From this perspective, these highly mathematical models seem not to agree with the steering behaviors of real pedestrians. Other drawbacks of these methods include the lack of distinction between multiple optional velocities for collision avoidance [237]. It is challenging to define a single cost function that distinguishes the consequences of various

optional actions in dynamic situations. Because of the precision in the mathematical formulation, collisions can always be prevented. As a result, the simulation results in certain situations would be too artificial compared with pedestrians behaviors we observe in daily life situation. For instance, perfect symmetry can be generated in multiple agents' motion in a model to achieve smooth and collision-free movement. However, such a perfection (or optimization) from the mathematical point of view does not always work in the intended way to resolve collisions efficiently. As mentioned in [72, 147], lanes with different widths that form at different time naturally help resolve grid-lock situations in a counterflow situation in the middle of a narrow corridor. In summary, motion planning from a mathematical perspective is effective for collision avoidance, but may have no relation to pedestrians' natural steering and emerging behaviors. Therefore, they are mainly good for robotics navigation, or at the low level (i.e., physical layer) of crowd simulation to prevent collision only.

2.2.2 Physical Particle Approaches

Another branch of work in simulating crowd behaviors has been reported from the physics research community, where a particle system is usually used to model a crowd. Individuals are treated as particles driven by potential fields or virtual forces. Accordingly, there are two main approaches under this branch, the *field-based* models and the *force-based* models.

Field-based approach models the steering behaviors of pedestrians based on the geometrical representation of the environment on the required scale, and its implications on the behaviors of pedestrians. A typical example of the field-based approach is the Cellular Automata (CA) model. CA models divide the given space into discrete cells or grids. Entities then occupy these points and move through the simulation while avoiding other occupied cells [231]. The pioneering work of applying the CA approach in pedestrian simulation was done by Blue and Adler [18, 19]. In their work, the local movements of a pedestrian are modeled with a matrix of preferences which contains the probabilities for a move, related to the preferred walking direction and speed, toward the adjacent directions. Schadschneider introduced the interesting concept of a *floor field* to mediate the long-range interactions between pedestrians [182]. The field modifies the transition rates to neighboring cells. CA approaches were later used to simulate evacuation scenarios for large crowds and study pedestrian dynamics [25, 183]. The main advantage of CA approaches is that they provide a simple and quick way to measure the environment (through cells), and choose pedestrian's

movement based on a simple set of rules across the cells. However, due to the fact that cellular automata models always discretize the environment into regular cells, this approach may not be suitable for modeling a microscopic pedestrian simulation because of two main reasons according to [106]. First, it is unable to trace the movement of individual pedestrians with fine level details to create a visually pleasing fluent movement of pedestrians. Secondly, it focuses more on imitating the various pedestrian phenomena rather than representing the actual mental states of a pedestrian.

The extension of CA to plan the motion of pedestrians gave rise to methods based on various other forms of *potential fields*. Potential fields have been used in robotics [86, 101, 102, 117] and the simulation of pedestrians [110, 145] to control the entities to evade obstacles and move toward a destination. The approach of potential fields was generally used to generate a global field for the entire landscape where the potential gradient is contingent upon the presence of obstacles and distance to goal. Since a change in target or environment requires significant re-computation, these navigation methods are generally confined to systems with non-changing goals and static environments. This method is also subject to *local minima* problems and does not necessarily reach the goal.

At the local path determination level, variants of potential field methods have been applied to move a simulated pedestrian while avoiding collisions dynamically with others in the near surrounding field. Treuille et al [212] proposed a collision avoidance model using the concept of dynamic potential fields and discomfort field to reflect the agents' personal preferences in path selection in their continuum crowd model. Feurtey's pedestrian collision avoidance model used a collision zone concept derived from the agent's vision of the environment [47]. Huang [83] proposed the visual navigation and obstacle avoidance model using a steering potential function of agents. More recently, Kapadia et al [95] proposed the concept of affordance field and modeled the field around an agent in an egocentric manner. A common feature of these methods is that the behaviors of a pedestrian is governed by the "potential" function according to the perceived status of different fields in the environment [111].

Another approach controls the motion of pedestrians based on forces rather than fields. Physical or virtual forces between individual entities are artificially introduced to affect the motion according to Newton's Second Law of Motion [142]. Applying such an approach to pedestrian simulation, each individual pedestrian is modeled as a particle. The interactions between them are modeled as different virtual forces. A typical example of this approach is the social force model proposed by Helbing [69].

In this model, individuals repulse away each other and are attracted towards the goal. The repulsion and attraction is modeled as so-called “social forces”. Many models have extended the basic social force model to address different issues in pedestrian simulation. They can be used to simulate basic pedestrian navigational behaviors such as steering and pushing behaviors among agents by introducing the pushing forces in addition to the existing forces [113]. Kirchner et al [103] modeled the queuing behaviors of pedestrian in a dense crowd situation through a friction factor. There are several advantages of this approach in its application in pedestrian simulation, in particular, for the massive crowd in dense scenario. Firstly, individual pedestrians can be modeled with full degree of movement freedom (compared with the field-based methods, where the motion of a pedestrian is limited by different fields). Secondly, appealing simulation result can be achieved based on internal (self-driven) and external (social) forces. Thirdly, variable forces can adapt to different situations dynamically. As a result, this approach is widely used in modeling interaction between pedestrians as simple attracting and repulsive forces [71, 97]. However, there are also several disadvantages from the perspective of realistic simulation for individual pedestrians. First, many of the forces are created artificially to generate appealing simulation results in these models. It is thus difficult for modelers to relate the virtual forces with real pedestrians’ behaviors. Secondly, the simulation results of such an approach is highly sensitive to the parameter values to define different types of forces. Consequently, the parameter calibration is a challenging task. For example, deadlock may arise in the simulation as a consequence of conflicting forces. Thirdly, the nature of forces results in frequent oscillation in a simulated pedestrian’s trajectory, if there are multiple and dynamic forces affecting, which looks unnatural at the individual level.

2.2.3 Agent-based Approach

Agent-based modeling is another popular approach in crowd simulation. An agent-based model simulates each individual pedestrian as an agent based on some elementary form of intelligence (i.e., sensing, decision, and action capabilities) for each of them. Decisional (i.e., how to make decisions) and behavioral (i.e., how to act) rules are usually specified in these models to control an agent’s behaviors as a consequence of its decision-making process [15, 99]. Since each agent is independently modeled based on their unique attributes and rules, it is autonomous to behave differently based on its own decision. Thus, agent-based models are suitable for microscopic pedestrian simulation.

Many existing microscopic models were proposed to simulate human navigational behaviors [114, 124, 139, 186, 217, 218]. Most of these models simulate various behaviors based on certain predefined rules. A typical example of rule-based approach in modeling the steering behaviors is Reynolds' *boids* model [168]. The boids model was initially proposed to simulate various behaviors of birds, and later has been adopted to model the steering behaviors of pedestrians [169]. In his work, Reynolds has divided motion behavior into three levels as action selection, steering and locomotion in a hierarchical way. Three simple rules, *separation*, *alignment* and *cohesion* were defined to navigate autonomous boids around their world in a life-like and improvisational manner. A list of steering behaviors such as seek, flee, pursuit, evasion, flocking and lead following have been implemented in his work. While easy to implement and capable of generating realistic birds' behaviors, his steering model is not intuitive to explain various navigational choices of individual pedestrians.

Other works also proposed different behavioral rules to simulate the collision-avoidance behaviors of pedestrians realistically. In [124], different rules are applied to different types of collisions (determined by relative position of two colliding agents). Similar model has been developed by Shao et al [186]. In their model, agents will execute subroutines according to specific inter-agent collision types. These models can generate seemingly realistic simulation results through careful examining on the tangible factors such as the positional information of pedestrians' movements. However, most of them have not taken personal traits of a pedestrian into account when designing the decision rules. In particular, psychological factors of different persons are not considered in most of these models.

Recently, psychological and social factors are incorporated into the behavioral rules of various models. Rymill and Dodgson worked on human behavioral model with focus on the mental states of individual agents. They have extended their original work to propose a psychologically-based behavioral model [174], and improved it by implementing a psychologically-based vision and attention model [175]. Their model is heavily dependent on psychological studies of pedestrians, which provides theoretical support for the validity of their model [174]. Sakuma et al [178] implemented a psychological model for animating crowded pedestrians. In this model, the decision-making scheme controls plausible avoidance behavior depending on the positional relations among agents on the basis of a two-stage personal space and a virtual memory structure as proposed in social psychology. Luo et al [126] have worked towards a generic behavior modeling framework for crowd simulation. Psychological

factors such as the emotion of individuals during the emergency evacuation process are included in their framework [8]. In [155], prediction is taken into account. The synthetic-vision based model described in [148] follows a *visual stimuli/motor response* control flow by taking captured image from the real world as input to form the visual stimuli. Although these models have achieved better simulation realism by taking psychological factors into account, there is still space to improve.

First, predefined rules in the model are likely to be tightly coupled with specific scenarios. Therefore, some parameters defining the rules need to be frequently adjusted to make the model capable of generating realistic behaviors from one scenario to another. Such models may also perform inefficiently in run time because it needs to take into account a large number of factors and rules to cover a wide range of different situations (normal or emergent).

Secondly, as these models feature different sets of rules to model different behaviors of a crowd, there is a paradox between the system complexity and the realism the model can achieve. With a small number of rules, it is difficult to capture different aspects of crowd behaviors, but the system can be kept simple. As realistic crowd behavior patterns can change significantly from one scenario to another, more rules have to be introduced to capture these different behaviors. It is a challenging task to organize and coordinate different rules. Constraint by the rule set, such a model may not be flexible or extensible.

Besides, some utility-maximizing rules are generally used to generate the optimal rational decision of an agent in existing work. For example, in [178], they have defined mental stress based on positional relationship among pedestrians as one of the measurements to guide their route choices. From the utility point of view, their choices will be determined by the minimal mental stress value. Although it is a feasible way of formulating personal choices into computer models, the definition of the virtual utility affects the realism of the model significantly in this approach. Since there is no standard way of measuring such utility, it is difficult for modelers to specify different behavioral rules in different scenarios. As a result, the simulation results of such a model hardly turn out natural and realistic unless tremendous trial-and-error testing is carried out in the calibrating process.

Lastly, existing models handled collision avoidance mainly through prioritized comparisons between pairs of agents in a sequential manner. One agent will need to compare its speed and direction with each of the potentially colliding counterparts sequentially in order to reduce the range of available options on its navigational

choices. By accurately calculating the amount of detouring in speed and direction, it can generate collision-free paths for each agent, similar to the motion planning approaches from the robotics research. However, such an approach does not reflect the natural cognitive process of pedestrians for two reasons. First, it seems that pedestrians can quickly assess the situation by sensing and processing a large number of neighbors at the same time. A gestalt [107] (or the organized whole), rather than individual components of a situation is more likely perceived by a pedestrian and thus affects her behaviors. From this perspective, the simple integration of pair-wise interaction in a sequential manner may not accurately reflect the cognitive process. Second, pedestrians do not always move without collisions, which means they probably do not calculate their motion precisely based on what they perceive. From these perspectives, the perception and cognitive capability of a pedestrian has been largely omitted in these models.

In summary, agent-based approach is promising in modeling each autonomous entity with sensing, decision and action capabilities. Different rules can be applied to define the decision-making process and the corresponding behaviors. However, rules are likely tightly coupled to specific scenario conditions, thus such models may not function well in general. How to coordinate and organize different rules in a unified and effective manner is an important but challenging research issue. In addition, various psychological and cognitive factors should be considered in a model to increase the realism of a simulation model. We believe that human-like behavior should be generated by human-like mechanisms. Existing works largely omit the modeling of human perception to mimic a naturalistic cognitive process of a pedestrian, which make them insufficient for generating human-like steering behaviors.

2.2.4 Data-driven Approach

Data-driven approach has been proposed to address some of the problems in the existing agent-based models. For example, it is difficult for modelers to specify a reasonably complete set of rules to cover the complex behaviors of pedestrians. The data-driven approach tries to automate learning in the system in order to assign a behavior to an entity through matching its current state with corresponding behavior sets in the existing data.

Example-based approaches have been proposed and applied in steering behavior simulation [118, 120]. Real-life examples of the moving trajectories of people are recorded, extracted and stored as the input to a simulation model. Agents in the

simulation analyze the simulation environment and compare it with the stored examples. Certain stored moving trajectories in the example situations are applied. Although this work focused on replicating realistic steering behaviors, the model realism is limited as paths for agents are explicitly synthesized. Only external factors can be extracted from the image or video based examples, unique traits of individual persons are difficult to incorporate with this approach. In addition, the examples in existing work are defined directly with some low level parameters such as the (relative) positions of other agents and objects surrounding a target agent, the actions (in terms of moving direction and speed) being taken by the target agent, etc. Consequently, thousands or even hundreds of thousands of examples are needed to reproduce a variety of crowd behaviors. Significant effort is needed in pre-processing the recorded videos. The computational cost of such an approach is also very high because of the large number of low level actions existing in the real data.

2.3 Summary

Pedestrian simulation is widely used in various fields such as urban planning, safety evaluation and crowd simulation. For real-time applications, the realism of the model is a critical issue that has drawn much attention from researchers in not only computer science, but also other areas such as psychology and sociology. In spite of these efforts, it remains a challenging research topic. My research focuses on generating realistic navigational behaviors of pedestrians in various normal life situations. To make the model capable of reflecting human-like intelligence in their navigational behaviors, research needs to be carried out in multidisciplinary fields. As a result, I have divided the literature review into two parts.

First, it is believed that a good model should represent various pedestrian characteristics realistically. Therefore, I have reviewed studies on pedestrian characteristics to describe and explain their various navigational behaviors. Although this work focuses on microscopic pedestrian simulation, I have also briefly reviewed macroscopic pedestrian characteristics such as average walking speed and pedestrian density to help understand pedestrian movement on an aggregate level. Microscopic pedestrian characteristics were then reviewed in detail. Studies from ergonomics were first reviewed to provide some empirical data describing the space requirement and speed limit for pedestrians. Microscopic pedestrian characteristics from different aspects, such as vision and attention, spatial perception, cognitive process and behavioral habits of individual pedestrians were then investigated to find relevant theories that

explain pedestrians navigational behaviors. These works provide theoretical support for the design of our model.

In the second part of this chapter, I have reviewed four typical approaches from the existing work to simulate pedestrians' navigational behaviors. Each approach is found to be suitable for certain applications, but limited in others. The robotics-based approaches aim at finding optimal collision-free paths for all characters rather than imitating how real pedestrians behave; the physical particle-based approach treats each individual as a particle/entity, whose motion is controlled by various forces or fields. Such forces and fields are virtual and do not exist in real life. Thus it is not easy for a modeler to tune these forces. The agent-based approach is similar to particle systems, but differs in the sense that it treats each individual as an autonomous agent with sensing and decision making capability.

However, existing approaches still suffer from a similar problem, that is, different rules are difficult to tune and organize. The data-driven approach on the other hand, aims at driving the simulation with recorded example movement of real pedestrians obtained from images or videos. Unfortunately, using such examples we can only "synthesize" their movements from the examples, and cannot extract the internal states of pedestrians. Furthermore, they can be computationally expensive if the example base to search is large.

In summary, existing approaches have their own disadvantages in generating realistic navigational behaviors of pedestrians, especially as the natural consequence of a realistic mechanism that likely reflects the cognitive processes of pedestrians. Since the rules and virtual forces are far from the way that a person describe how he moves, it is also difficult to develop and use such models from the modeling point of view. In real life situations, pedestrians are quite efficient when moving among crowds without dedicating much effort on their motion planning. We want to investigate the reasons for such observations, and aim to imitate how they behave. We also aim to address some of problems with existing approaches, and to propose a method that will generate realistic navigational behaviors through modeling the natural cognitive processes.

Chapter 3

Theoretical Basis

In this chapter, we describe and explain the idea of *local path determination* of pedestrians, which forms an important layer in the simulation of navigational behaviors described in this thesis. We will begin with some assumptions that form the basis of this model and explain why we make these assumptions. The hierarchical motion modeling structure as mentioned in Chapter 1 is then discussed in detail to tackle the complex navigational behaviors through three layers, of which the *local path determination* lies at the intermediate layer. Central to the assumptions made is that realistic strategic steering behaviors of pedestrians could be generated through careful imitation of the cognitive processes of humans. The *perceive-decide-act* paradigm is then discussed in detail for its use in an agent-based model to represent the cognitive processes of a human being.

3.1 Assumptions on Navigational Behaviors

In this section, we make two assumptions to facilitate the modeling of pedestrians' navigational behaviors in this thesis. These assumptions are proposed based on some of the previous pedestrian work reviewed in the previous chapter, together with our own observations on pedestrians' navigational behaviors in real life situations.

As can be observed in one's daily life, pedestrians do not change their speed and direction frequently in order to avoid collisions. As found by Dalton [37], *angular minimizing rules* can be observed in pedestrian navigational behaviors. Pedestrians generally walk in smooth paths and collisions seldom occur. Such a phenomenon does not necessarily imply that pedestrians use some smart mechanism to guarantee their collision-free movements. While the reason for such an efficient motion remains debatable, pedestrian studies help describe and explain such behaviors from different social and psychological perspectives.

As reviewed in Chapter 2, previous pedestrian studies [30, 54, 230] have described a set of pedestrians’ navigational behaviors. Such behaviors include “matching speed and route of others in front of them”, “overtaking others in front in order to move faster”, and “detouring as soon as oncoming people are detected in order to avoid collisions with them”. We tried to understand pedestrians’ navigational behaviors through these studies and have identified three common characteristics of such behaviors that distinguishes them from others. Firstly, such behaviors occur frequently and repeatedly among pedestrians. Pedestrians seem accustomed to perform such “routine behaviors” under similar situations subconsciously. Secondly, these behaviors indicate a *planning*-like capability of pedestrians when they steer among crowds. Such planning-like capability is reflected through their deliberate and early adaptation of their maneuvers. In accordance with the strong aversion to close contact, planning helps people avoid each other as well as to minimize angular changes during movement to save effort [54, 230]. Thirdly, such behaviors are usually performed through a sequence of actions with tentative cognitive control to coordinate them. We refer to such seemingly planned behaviors adopted by pedestrians frequently and repeatedly, as *steering strategies* in this thesis. We believe that pedestrians do not make complex decisions in order to avoid collisions at each step in their movement; instead, they often apply simple yet efficient steering strategies under different situations to plan their movement through a sequence of actions to avoid potential collisions in advance and thus to achieve smooth movement.

Although steering strategies are commonly adopted by pedestrians to minimize the chance of collisions with others, exceptions do occur in many situations. Reasons such as attention pretermission, wrong prediction and unexpected incidents generally result in collisions in these situations. For example, at the corner of a cross passage, two pedestrians may not be aware of each other when moving fast until the collision is *imminent*, i.e. in a short distance with little reaction time. In such a case, the planned steering behaviors do not keep the pedestrian from collisions. To resolve an imminent collision, pedestrians may react to the situation *instinctively* to prevent the physical collision. For example, when a person suddenly realizes that he is about to collide with someone, he may suddenly stand still, or slide his body significantly, or even jump aside to avoid a severe collision. In general, we refer to these behaviors which help resolve an imminent collision at the last moment as *instinctive reaction*. From the psychological perspective, when pedestrians have to perform instinctive reactions, they may already be in a situation where their *personal space* [200, 216] has been

violated and their *mental stress level* [178] is already relatively high. Most people seem likely to start steering early so as to keep their *dignity* [54] and to avoid close contact with others even though actual collision has not occurred.

Besides strategic steering behaviors and instinctive reactions, people are also sometimes observed to move in a rather impromptu manner, which may not involve any planned behaviors by deliberately adopting steering strategies. In such cases, little if not any cognitive effort is involved in motion planning. They react to the surrounding situations at each step as they move. In this study, we refer to such movement without cognitive planning of their route as *non-strategic motion*, which is in contrast to the behaviors described as steering strategies. There are normally two kinds of situations where non-strategic motion is likely invoked. In the first kind of situations, pedestrians may not pay attention to the surroundings for the collision avoidance purpose, thus they do not *intend* to apply any steering strategy. For example, when pedestrians are reading a newspaper or window shopping while walking, they often do not pay much attention to avoid collisions with other people. In the other kind of situations, the pedestrian is unable to apply any suitable steering strategy to a situation, even though he pays attention. This may be because he lacks of experience to handle similar situations previously. In such a case, non-strategic motion is adopted as a trial-and-error approach to lead the pedestrian through a crowd.

While strategic steering behaviors, instinctive reactions and non-strategic motion are all the common maneuvers observed in the navigation process of pedestrians, they are invoked in different occasions and are performed by pedestrians in different ways. By applying steering strategies, pedestrians move in smooth paths while trying to avoid collisions with other pedestrians. Such steering behaviors are proactively and deliberately performed by pedestrians to achieve their goal of collision-avoidance during navigation. Instinctive reactions complement strategic steering behaviors by acting as a last-resort collision avoidance mechanism, which comes into force at the last moment in the steering strategy execution process, when a selected steering strategy can not keep the person from collision. Non-strategic motion involves no planning in their movement. The pedestrian moves and avoids collisions reactively to the situation at each step. As a result, frequent and significant changes in the velocity of the pedestrian are more likely to occur.

To describe and summarize these observed navigational behaviors of pedestrians, we make the following assumption:

Assumption 1: *Pedestrians tend to proactively and deliberately apply certain simple steering strategies to minimize the chances of performing instinctive reactions for avoiding imminent collisions. Moreover, steering strategies help pedestrians move smoothly by planning their steering behaviors in advance of potential collisions as opposed to non-strategic motion.*

This assumption has two implications to the model architecture:

- We consider motion to mostly take place through strategic steering behaviors that will minimize chances of collision. Instinctive behaviors only step in as an emergency measure to avoid imminent collisions when a specific steering strategy is selected. Non-strategic motion is involved when no steering strategy is invoked.
- Instinctive reactions are generally simple and largely similar, and thus heterogeneous characteristics of navigational behaviors are mainly due to different strategic steering behaviors. In addition, with good steering strategies, instinctive reactions and non-strategic motion, which may result in more frequent and significant changes in their moving speeds and directions of pedestrians, can be effectively minimized as is observed in real life. Therefore, our design focuses on the modeling of steering strategies that pedestrians usually apply in various real life situations.

Pedestrians repeatedly adopt similar steering strategies in similar situations. This may be because they have learnt various steering strategies from their past experience in resolving collisions under these situations. In terms of their steering behaviors, *experience* may influence pedestrians in two ways. First, individuals with different experiences may have different sets of steering strategies stored in their long-term memory. Secondly, even with the same set of experiences, individuals with different experiences likely schedule and execute various steering strategies in different ways. Pedestrians are generally experienced walkers in most normal life situations. However, heterogeneous navigational behaviors are still commonly observed. In this respect, experience variation in the set of steering strategies for different pedestrians may not be significant. It is the different ways of adopting common steering strategies that result in the different behaviors. Such variations in scheduling and executing a set of steering strategies may be attributed to different factors such as cultural differences and behavioral habits of individuals [36, 170, 199, 226].

Although pedestrians may apply different steering strategies in different situations, a limited number of steering strategies are commonly observed in daily life such as *follow*, *overtake* and *side-avoid* [36, 230]. We believe that these three steering strategies are most commonly adopted by pedestrians in various normal life situations. By proposing these steering strategies, we do not attempt to argue that only these three are adopted by pedestrians in all the situations. On the contrary, we believe that people naturally adopt a different set of steering strategies in different scenarios. However, our research focus is not on how people choose the set of steering strategies corresponding to different scenarios. Instead, the research emphasizes on the importance of experience on scheduling and executing a limited number of simple steering strategies, with the right timing and adjustment, in achieving efficient steering behaviors. For simulation purposes, we construct a steering strategy pool with these three steering strategies in our model. Model developers are expected to use different steering strategies in their models, which can easily be extended based on the architecture that is discussed in Chapter 5. With respect to the discussions above, we have made another assumption:

Assumption 2: *A small number of steering strategies are sufficient for pedestrians to move smoothly and to avoid collisions efficiently in various real life situations through scheduling and executing these steering strategies properly based on their experiences.*

This assumption suggests a modeling approach to address the importance of *experience* in the cognitive processes and thus to generate naturalistic steering behaviors of agents.

In summary, we have studied pedestrians' navigational behaviors and proposed two assumptions accordingly. Such assumptions have implications on the design of our model mainly in two aspects: First, a hierarchical structure can be adopted to model the navigational behaviors of pedestrians in three layers, in which, the strategic steering behaviors at the middle layer play an important role in people's navigational behaviors and they will be our modeling focus in this research. Secondly, the importance of experience of individual pedestrians in scheduling and executing steering strategies under different situations is to be addressed in the model.

3.2 Hierarchical Motion Modeling Structure

Based on **Assumption 1**, we propose to tackle the modeling of complex navigational behaviors through a hierarchical motion structure. Instead of the traditional

bi-layer structure, a tri-layer hierarchy of the motion system, which consists of “path planning”, “local path determination” and “locomotion” is proposed as mentioned in Chapter 1. In this section, we focus on describing the behaviors involved at the “local path determination” layer and their relationship with the other two layers in detail.

Figure 3.1: A tri-layer hierarchical motion in modeling navigational behaviors.

The tri-layer motion modeling structure is shown in Figure 3.1. As the input, one or several *goals* are passed into Layer 3, the “path planning” generates an estimated

preferred velocity to goal V_g of the agent towards its immediate subgoal, a waypoint in a path. Layer 2, the “local path determination” takes V_g as an input and generates the output, a sequence of computed preferred velocities V_p^i corresponding to simulation step t_i to characterize the execution processes of a selected *steering strategy*. When no steering strategy is selected, V_p equals V_g for each simulation step. At Layer 1, the *motion control mechanism* takes the generated V_p from Layer 2 and generates the output as the *actual velocities* V_a^i for the current simulation step t_i . V_a^i may or may not equal V_p^i and the difference can be relatively large or small as will be discussed in detail later. The generated actual velocity will then drive the agent in the simulation to move in the virtual environment.

As mentioned in **Assumption 2**, for most normal situations, strategic steering behaviors are performed through executing a small number of steering strategies, which forms a *steering strategy pool* as shown in Figure 3.1. The steering strategy pool contains k steering strategies S_1 to S_k that pedestrians usually adopt in a specific scenario. From the steering strategy pool, a specific steering strategy S_i is selected by the agent to direct itself towards the target waypoint, with the estimated preferred velocity V_g , while trying to minimize the chance of collisions with other agents in the environment. A steering strategy is usually executed as a sequence of planned actions in several phases, which in turn is specified by a sequence of preferred velocities from V_p^0 to V_p^N for the simulation period of T_0 to T_N respectively. For example, an *overtake* steering strategy can be executed in two phases as *catch-up* and *surpass* (and optionally with the third phase: *resume original course*) from the modeling point of view. For each of the phases, a preferred velocity can be generated for the period of time representing the phase accordingly. Such a sequence of preferred velocities along the route has to be planned T time steps before the current step, hence our reference to it as a *strategic steering behavior*. The selected steering strategy S_i is then executed through a sequence of instructions. At each simulation step t_i , an *actual velocity* V_a^i of an agent is generated based on the preferred velocity V_p^i for the simulation step t_i and the motion adjustment mechanism (e.g., such as RVO, social force etc) at the “locomotion” layer. As discussed in Chapter 1, most of such motion control mechanisms will generate an “optimal” velocity that guarantees a collision free route for the agent. V_a^i may or may not be consistent with the preferred velocity V_p^i as specified by the steering strategy S_i . One possible reason for such a difference would be subjective prediction of others’ movements. Some pedestrians are likely to predict other people’s movement better, and thus form a more comprehensive perception of

the situation over time. Consequently, the selected steering strategy by them is likely to be executed more smoothly as specified by the preferred velocity V_p^i . Such a “well” planned steering strategy S_i is reflected by a higher probability of the actual velocity being equal to the preferred velocity in the simulation. We refer to such motion directed by the preferred velocity as the *strategic motion* at the locomotive level. In other cases, V_a^i differs from V_p^i . If the difference between the two velocities is small, the motion mechanism is used to adjust the selected steering strategy and continue to execute it. Such a minor adjustment does not change the selected steering strategy and can be commonly observed from the movement of pedestrians in real situations. We refer to such motion as the *adjusted strategic motion*. When the difference between the two velocities is larger than certain value, the steering strategy is not effective in resolving potential collisions. In such a case, the agent adjusts the actual velocity V_a^i and violates the current steering strategy. The agent will re-assess the situation and select new steering strategies (if any) at the next simulation step. Such motion of agents simulates the *instinctive reactions* of pedestrians as discussed above. The other type of motion at this locomotive layer is the *non-strategic motion* as discussed in the last section.

In summary, the “local path determination” layer takes a velocity V_g from the “path planning” layer as the input and produces the preferred velocities V_p as the output. V_p may equal V_g when no steering strategy is selected, or different when it is used to characterize a selected steering strategy. V_p are then passed to the “locomotion” layer to generate a sequence of actual velocities V_a^i for each simulation step t_i to move an agent in the simulation. Based on the condition of whether V_p equals V_g , whether V_p equals V_a and how much V_p differs from V_a , we use four terms to represent different types of motion as shown in Figure 3.1. Such differentiation helps describe various movement behaviors of pedestrians and can be applied in the design and evaluation of the model. Such a hierarchical modeling structure has two main advantages:

- It naturally follows the way pedestrians make decisions during navigation. Since human behavior is highly context dependent [64], humans tend to apply different “strategies” in different perceived situations. It is natural for pedestrians to select relevant steering strategies properly before considering how exactly to execute such strategies in terms of a sequence of actions. For example, in a dense crowd, pedestrians may first select the steering strategy to *follow* the pedestrians in front of them. They probably will not decide on who to follow

and how to follow, until they select to follow. Such a hierarchical division of navigational behaviors reflects the layered cognitive process of humans [208].

- It simplifies the modeling of complex navigational behaviors from the modelers' perspective. On one hand, behavioral complexity can be reduced from the top-down division of the hierarchical structure so that the modelers can focus on each of the behaviors with less complexity. On the other hand, it avoids the complicated fine tuning of various influential factors that can directly affect the movement of the agent at the locomotive level. As discussed in Chapter 1, existing motion planning models are mainly based on virtual forces [69] or other mechanisms [169, 219] that directly manipulate the actual velocities of an agent to avoid collisions with other entities. While being useful in large-scale crowd simulation, it is not always easy for the model designer or user to understand complex navigational behaviors directly from the basic locomotion of individuals. In the real world, behavior are more often described in a higher level than the locomotive level. For example, we describe "*pedestrian A is overtaking pedestrian B*" instead of saying "*pedestrian increases his moving direction by x degrees to the left/right side of pedestrian B, then speeds up by y meters per second and changes his direction again by z degrees etc.*".

In this section, we have discussed the tri-layered hierarchical structure that can be used to model complex navigational behaviors of pedestrians more easily and naturally from the modeling perspective. In this structure, our model will focus on the navigational behaviors at the middle layer, which mainly involves the strategic steering behaviors.

3.3 *Perceive-Decide-Act*

In the previous sections, the strategic steering behaviors of pedestrians at the middle layer of the proposed hierarchical motion modeling structure was discussed. As explained earlier, *experience* is important in scheduling and executing various steering strategies through the cognitive processes of an individual pedestrian. In this section, we address the issue in modeling the cognitive processes of an agent from the perspective of .

We choose to replicate the behaviors through the imitation of the cognitive processes that are possibly involved in their steering process. agent-based modeling

(ABM) is a promising approach in modeling human cognitive processes and behaviors. In this context, each agent generally follows the *Perceive-Decide-Act* paradigm¹ that is invoked iteratively in the simulation. In each cycle, an agent perceives and obtains information from the environment, makes decisions based on the cognitively processed information that helps achieve its goals, and carries out a course of actions to execute the decisions.

An agent senses the information from the environment and generates a set of *percepts* [173]. In some existing ABMs for crowd simulations, the *perceive* process mainly focuses on the sensing function of the agent. However, we distinguish the term “sense” and “perceive” in this thesis. A set of percepts represent the cognitive information that is directly usable for decision making. Percepts formed from sensing the situation alone cannot adequately represent the comprehensive information used for direct decision-making. Information filtering, prediction and aggregation is necessary in addition to the sensing function to be considered to form the decision criteria (i.e., percepts) in the perception process. To distinguish this decision process from the sensing process, we use *situation assessment* throughout the thesis to address the perception process in the model, where an agent senses and assesses the environment subjectively to form the cognitively processed percepts. In the context of pedestrian simulation in this thesis, we refer to such comprehensive set of cognitively processed percepts as certain forms of patterns recognized from the situation as will be discussed in the next chapter.

The *decide* process is important in an ABM system. From a traditional modeling perspective, the analysis of individual decisions of an agent is concerned with the logic, rationality and the invariant optimized choice it leads to [228]. Although decision-making frameworks [66, 156, 166, 239, 240] have been proposed, most of these previous methods focus on the mathematic logic rather than the imitation of the way human beings make decisions in real life situations. These models are commonly referred as *rational* decision-making models, which aim to generate the optimized output given a set of constraints and utilities. While such rational decision-making process is frequently involved in many utility-driven activities such as stock trading [3, 128, 243], it seems most decisions are made unconsciously or subconsciously for other activities such as navigation in a street in many real life situations. As discussed in [144], “*we simply decide without thinking much about the decision process*”. One of the possible

¹Another term, *Sense-Think-Act* paradigm [163] is also commonly used. They are similar in terms of representing the iterative process an entity (either robot or agent) performs in the research context. We use this term and stick to it in the whole thesis.

reasons may be the familiarity of the situation and *routine* decisions that have been repeated for times under such situations [29, 132]. The concept of *experience* was thereafter introduced by researchers [247] to represent such a cognitive process, where *experience* is suggested as an important component [172]. One of the well-known decision-making framework following the Naturalistic Decision-making (NDM) mechanism is the Recognition-Primed Decision-making (RPD) framework [104]. RPD emphasizes on the role of experience through the “recognition” process. Traditional approaches to the decision-making process have employed analytical rules to generate and compare options based on weighted features, while RPD focuses on the situational recognition as opposed to the feature-based comparison of options inherent in traditional approaches. Compared with other decision-making frameworks, RPD has advantages of rapid decision-making [104]. However, it may also suffer from severe failure in uncertain situations because it always chooses the first recognized course of actions without proper assessment. The RPD framework was previously applied in the military and aviation applications to simulate a subject’s decision-making process under time pressure [46, 146, 195]. The demanding situations in these applications address the importance of stress to the decision-makers. Efficiency and accuracy of the models are vital for these applications. Pedestrian simulation, however, is different from these applications. Pedestrian simulation mainly focuses on modeling navigational choices of pedestrians in normal-life situations. Most recently, in [127], RPD was used in crowd simulation to simulate realistic decision-making process of agents. However, their work focuses on some high-level cognitive processes such as the path planning of the crowd in a large-scale environment, which is different from our research scope described in this thesis. In this work, we utilize the concept of the RPD framework and model the experience of agents’ through a proposed pattern-matching mechanism.

The *act* process in the *perceive-decide-act* paradigm actuates the decisions made by an agent to take effect in the virtual environment. In the context of steering behavioral simulation, an actual velocity is generated eventually at each simulation step for the agent to move itself in the environment. As discussed in Section 3.2, we focus on generating preferred velocities according to different steering strategies at the middle layer in the tri-layered motion modeling structure. Such a preferred velocity is then passed to the bottom layer as an input. The actual velocities are generated as the output according to certain procedural instructions on the execution processes of a selected steering strategy in the *act* process of our model.

In summary, there are three main components as the perception, decision and action systems, which will be addressed in detail in the model design and development in Chapter 5.

3.4 Summary

In this chapter, we first discussed some of the observations and pedestrian studies on their navigational behaviors. Based on these observations and studies, we proposed two assumptions to describe and explain these behaviors and they form the theoretical basis for the proposed model in this thesis.

Based on the assumptions, we proposed a tri-layer hierarchical motion modeling structure. There are two main advantages of such hierarchical modeling structure. First, such hierarchy naturally follows the way pedestrians make decisions during navigation. Second, it simplifies the modeling of complex navigational behaviors from the modeling point of view.

In the hierarchical motion layers, we focus on the middle layer of behaviors, which are mainly informed by a set of steering strategies. By adopting different steering strategies in different situations, an agent tries to minimize the chance of collisions while moving relatively smoothly towards its goal. At the locomotive level, four types of motion have been defined based on whether steering strategies have been applied and whether the steering strategy directs the agent successfully to avoid collisions in the simulation.

To model the cognitive process and the steering behaviors of pedestrians, the *perceive-decide-act* paradigm has then been discussed under the context of ABM. From the discussion, we have identified several design issues for the model to address:

- *Situation assessment* is used to model the comprehensive perception process. Although some other works categorize the processing of perceived information into the *deciding* process, there are mainly two reasons we model it in the perception process. First, we want to emphasize on the perception (recognition) of the situation rather than the decision making process as suggested by the NDM mechanism [247]. Second, the processing of perceived information fits well into the pattern specification processes in our model.
- RPD with the emphasis on the experience of individual agents is a well-recognized framework to model the *decide* process of an agent. As the key concept in this thesis, spatio-temporal patterns are naturally involved in the recognition and matching processes under the proposed pattern-based approach, which is highly consistent with the RPD framework in the conceptual level.

- The *act* process of the model is to follow the tri-layered motion modeling structure with specific focus on the middle layer. In particular, different steering strategies and their execution processes will be developed in the model.

Chapter 4

Spatio-Temporal Patterns

As a key concept in this thesis, the term , has been mentioned in the *perceive-decide-act* cognitive process. This chapter defines in detail the spatio-temporal pattern concept, motivates its use and presents a method for its precise description and specification. Specifically, we will first examine some of the ubiquitous patterns in many aspects of life and review studies from different research domains to explain the human brain’s habitual preference for using patterns. The motivation of applying STPs in the cognitive process of pedestrians’ navigation will then be discussed. Several terms related to STPs, that will be used in the model, will be defined and the representation of an STP in the form of a stack of *slices* will be described. A novel Pattern Description Method (PDM) that allows modelers to define and specify an STP will then be presented.

4.1 Patterns in General

A *pattern*, in different contexts, is defined in various ways in the dictionary. Briefly, we can refer to a pattern as “*something* of recurring and predictable structure or manner” [150]. The *something* is also sometimes referred to as elements of a set of objects with similar and regular structure.

Patterns are perceived and used in many aspects of our lives. They are of various forms, such as mathematical patterns, visual patterns, spatial patterns, logical patterns etc. [149]. In many real world situations, we need to process a lot of information and utilize it to help us achieve some objectives. In order to make sense of the complicated information, the brain has a built-in pattern recognition mechanism [205], which continuously, unconsciously observes the world. As it processes new and complex data, it instinctively tries to make sense of it all by looking for the connections that the pieces would fit together and what they have in common. The repeated occurrences of a pattern help establish correlations and even causal relations between

the perceived patterns and certain consequences subjective to the person. As argued in [189], people view their environment and create meaning out of the patterns that *they think they see* in nature. Sometimes this causal relation really exists, but sometimes it may not. When it does exist, we have learned something valuable about the environment from which we can make predictions that can aid in future activities; for example, for our ancestors in hunting and avoiding predators in ancient times; and for us in driving safely, working productively and interacting effectively with people [24]. This process is what scientists called *associative learning* [50], which is fundamental to all animal behaviors, including pedestrian steering behaviors. Patterns play an essential role in such learning processes and other general cognitive processes occurring in the brain. Previous work in neural science and brain studies can provide some evidences as well [26, 27].

Studies on the learning mechanism in brains such as [27] have revealed a set of principles to encapsulate the ways in which different aspects of body, brain and mind participate in the learning process. Although these principles are proposed to enlighten the learning process, three of them are particularly relevant to our discussion on the way that the brain generally functions with patterns. The first principle states that *the brain is a parallel processor* highlighting the way the brain is able to concurrently process massive amounts of information necessary to complete a task. The second principle explicitly outlines the importance of patterns in the activities happening in the brain as *the search for meaning occurs through patterning*. They referred to “patterning” as the meaningful organization and categorization of information and they suggested that the brain searches for meaning by attempting to discern and understand patterns as they occur and giving expression to unique and creative patterns of its own. Furthermore, they believe that the brain will reject meaningless patterns with unrelated pieces of information. The third principle states that *the brain processes parts and wholes simultaneously*. According to this principle, people tend to process some perceived objects through the overall information as a whole [26, 27].

Inspired by the studies reviewed above, we could summarize the general cognitive process involved in the brain for most activities in the following way: the brain takes in many separate pieces of information in parallel and processes them simultaneously. This processing involves organizing and categorizing them in a meaningful way; while filtering out irrelevant information. The organized and categorized information is perceived as a whole and used in further cognitive processes such as decision-making. Such perceived information as a whole can be generally referred to as a pattern.

The tendency of using patterns may attribute to the experience that formed through long-term repetition of the occurrences of certain patterns and the corresponding consequences [24].

The use of patterns in the cognitive process has been recognized through research in different disciplines. In particular, researchers in neuroscience have made attempts to show that regions within brain cortices such as the prefrontal cortex develop moment-to-moment models for patterns of events occurring in the sensory environment [84]. With different degrees of violated repeating or alternating visual patterns, the images from the Magnetic Resonance Imaging (MRI) of prefrontal cortex show different levels of brain activities. These studies have shown that “the human brain really looks for structure in the world, which means the patterns allow us to extract regularity from the world” according to the author of [84].

More recently, vision scientists at Boston University and ART Computational Neuroscience Laboratories in Kyoto, Japan suggested that it may be possible to use brain technology to learn complex skills such as playing piano, or reducing stress with little or no conscious effort as shown in the movie “The Matrix” [190]. Their experiment suggested that “early visual cortex” are so plastic that mere induction of activity patterns are sufficient to cause visual perceptual learning. Similar to the work reported in [84], the brain activity patterns are involved through the presentation of image sequences to the participants and captured through MRI. This study has shown the importance of patterns in the visual perception learning process.

In summary, patterns of different forms widely exist in day-to-day activities and pattern recognition seems to be part of the intrinsic cognitive functions of human brains. The important role, of which patterns and pattern formation plays in the human cognitive process, has drawn research attention. Such a research trend helps position the work described in this thesis and motivates the use of certain forms of patterns as a way of describing the human cognitive process that is likely involved in their steering behaviors.

4.2 Spatio-Temporal Patterns for Pedestrian Simulation

In this section, we describe the use of the “patterns” intuitively to mimic the cognitive process that pedestrians tend to rely on for decisions on various steering strategies. We will first discuss the motivation of the pattern-based approach in this work and then define terms specifically related to the patterns used in this thesis.

4.2.1 Motivation

As discussed in the previous section, humans are adept at searching for patterns in many tasks involved in daily life situations. In the context of navigation, visual perception of the environment is essential for choosing routes and steering behaviors. Our work is motivated by two basic assumptions based on our observations and existing literature on pedestrian behaviors. It seems that pedestrians achieve efficient steering behaviors relying on certain implicit criteria to assist their decision [79, 80]. Such criteria need to reflect the perceived situation comprehensively (not only in the spatial domain but also in the temporal domain), yet in a succinct and compact form that can lead to fast effective decisions. It is also assumed that pedestrians' experience plays an important role in guiding them to behave in certain way to effectively achieve their objectives (e.g., moving towards the goal while avoiding collisions with others). We regard such implicit criteria they use in the cognitive process as patterns, which pedestrians visually perceive and rely on to select corresponding steering strategies in different situations.

By representing the perceived situation in the form of patterns, we try to mimic the comprehensive visual perception of pedestrians and the way they use such information to make decisions effectively during navigation. Since this thesis focuses on the *local path determination* layer in the hierarchical motion modeling structure (Figure 3.1), the selection and execution of different steering strategies is intuitively based on the matching result between the perceived patterns from the current situation and some prototypical patterns that they keep as empirical references in their experience base to guide their behaviors in similar situations. The complex cognitive processes involved in a pedestrian's navigation have been transformed into a pattern recognition and matching process, which naturally fits the concept of RPD, where experience and recognition of certain cues plays an important role in the whole cognitive process. In such a context, the perceived cues regarding the situation are represented as patterns; the prototypical patterns and the corresponding steering strategies represent different experience instances of pedestrians. In previous robotics research [2, 112], "spatiotemporal patterns" were applied to guide robots through static environments using landmarks. Despite the similar terminology, the patterns proposed in this thesis are used to drive virtual agents through highly dynamic environments, focusing on a different layer of motion, which we would argue is a far more challenging problem. In addition, the dynamics of the agents are also considered in the pattern proposed in this thesis. In other words we not only look at the current spatial configuration, but also project future spatial configurations based on the perceived velocity of agents.

4.2.2 Definitions

In Chapter 3, we have described the concept of steering strategies that pedestrians apply in many different situations. The central idea is that a number of different perceived situations will lead to a few steering strategies. We have now given the notion of “perceived situation” a more precise definition in the form of a *Spatio-temporal Pattern (STP)*. Essentially we define:

STP: is a pedestrian’s perceived local spatial configuration (including other nearby pedestrians or obstacles in the situation) and how that changes over time

There are two forms of spatio-temporal patterns used in the cognitive process: the *concrete* STP and the *prototypical* STP defined as:

Concrete STP : represents a currently formed STP through sensing and perception from the situation.

Prototypical STP (or wildcard STP) : is a form of STP which can match a number of different *concrete STPs*. In other words the prototypical STP has the same structure as a standard STP, but with some spatial and temporal characteristic not defined.

The two different forms of STPs are formed in different ways. A *concrete STP* is formed at run-time for each agent through its visual sensing and perception process. Whereas a *prototypical STP* is defined by modelers to mimic the experience of pedestrians in the way that a prototypical STP usually leads to the adoption of a certain steering strategy. A *prototypical STP* is not necessarily concrete because only the prototypical characteristics of the situations are supposed to be reflected by such a pattern.

4.2.3 Pattern Representation

To represent an STP explicitly, some description method is needed. An STP can have different forms of representation according to different description methods. There are trade-offs between generalization and specificity of a description method and the corresponding forms of representation of an STP. In general, an STP’s representation needs to be general so that it can succinctly represent a group of similar situations, while at the same time specific enough to distinguish a particular situation appropriately. One could use natural language to describe and represent an STP in the text

form. By describing an STP using natural language, it is intuitive for modelers to understand the concept and thus to design a prototypical pattern corresponding to a steering strategy to imitate the experience of the pedestrians. For example, modelers can describe an experience instance as “there are people in front of me, walking the same way, they are walking at a slower speed and they are blocking my way to overtake.” Thus, a prototypical STP corresponding to the *follow* steering strategy can be extracted from the situation. Although natural language is intuitive for people to describe a situation, there are several drawbacks from a modeling point of view. First, natural language is notoriously ambiguous, and it usually contains many qualitative and fuzzy terms that reflect the higher level cognitive perception of a person on an object or situation. Secondly, it is difficult to decompose such terms into low-level quantitative components that can be modeled and measured properly. This emphasizes the challenge of finding the appropriate balance of generalization and specificity. For example, detailed information on the spatio-temporal configuration of the environment is difficult to describe in concise language. Lastly, it costs modelers’ effort to convert an STP that is described in natural language into machine-readable codes for the purpose of modeling, which, to some extent negates the beneficial intuitiveness of natural language description.

On the contrary, pattern representation using visual diagrams provides direct impression of an abstract concept to the modelers. In this thesis, an STP is represented in the form of a *stack of slices* as shown in Figure 4.1.

An STP indicates the perceived situation in terms of its spatial configuration (through visual perception as shown in Figure 4.1(a), 4.1(b)) and the predicted changes of such configuration. Each slice represents the particular perceived spatial configuration of the situation and the *stack* of consecutive slices indicates the predicted change of such spatial configurations for a period of time. A slice is further divided into different *rows* and *columns* to correlate different areas of the slice with the corresponding spatial areas as visually sensed by a pedestrian. Through these rows and columns, a slice is partitioned into a number of cells, each of which we refer to as a *section* of the slice.

In the example shown in Figure 4.1(c), the first slice p_0 represents a pedestrian’s perceived spatial configuration of the situation at the current time instance t_0 . The remaining slices (from p_1 to p_n) represent the predicted spatial configurations corresponding to the predicted time instance at t_1 to t_n . Through such a representation, a slice can be used to naturally represent the perceived space in front of an agent.

Figure 4.1: STP representation and formation as a synthetic visual perception process.

Such a representation can be easily integrated with the sensing and attention system of the agent. In addition, such a form also allows the hierarchical matching between two STPs in both the spatial and the temporal dimension.

Existing work on steering behavior modeling has adopted approaches such as *po-*

tential field [47, 83, 95] and *cellular automata* [18, 19], with emphasis on the geometric model of the environment and its impact on the steering choices. The slice-based representation of an STP in our work is related to such work as an STP specifies the perceived information of the environment. However, there are several differences between these approaches and the STP proposed in this thesis, giving us several benefits. First, a slice is used to indicate the cognitively processed spatial information through synthetic vision and attention (as will be discussed later) of the person, rather than the environment itself as modeled in the previous geometric models. Each *section* in a slice is associated with the estimated area in the actual environment space. Such estimation allows an agent to handle uncertainty through a hierarchical pattern matching process. Secondly, the temporal information is intrinsically reflected through the change of values along a stack of consecutive slices in the representation, allowing an STP to naturally support efficient space-time planning and steering choice selection, which is difficult to integrate into global fields in the previous geometric models. Thirdly, a stack of slices contains the spatial and temporal information of both the environment and other agents in a self-contained representation, which naturally reflects the feature of a pattern as a single and comprehensive criteria for efficient decision making as discussed previously. In addition, such a representation provides an intuitive direct impression for the modelers to visualize and design different prototypical STPs to mimic pedestrians' different steering experiences. Lastly, an STP represented in the form of a stack of slices can be easily modeled using corresponding data structures such as a matrix or an 3D-array for the modeling purpose. Note that the representation of an STP discussed in this section should be differentiated from the STP specification from the modeling point of view (see section 4.3).

4.3 Pattern Description Method

We have defined the spatio-temporal patterns and their representations in the visual form of a stack of slices in the previous sections. In this section, we propose a for modelers to *specify* an Spatio-Temporal Pattern (STP), in particular, prototypical STP, as such patterns need to be designed to mimic the experiences of pedestrians. Specifically, we address how to transform a conceptual STP in its visual representation to a form that can be modeled and programmed for the modeling purpose.

4.3.1 Overview

PDM can be viewed as a specific form of *language* that is generally used for informative, expressive and directive purposes [31]. In the context of this work, PDM is used to describe an STP (informative), to provide guidelines for model developers to specify an STP (expressive) and to allow agents to use STPs to generate steering choices in the simulation (directive). Similar to the natural language that has *vocabularies* and *grammars*, PDM also includes the necessary components. Specifically, PDM consists of the following components:

Vocabulary: is a collection of defined constant values and operators, from which the semantics of a particular aspect of the situation can be described and manipulated. In the navigation context, different constant values represent different perceived spatial constraints of the environment; operators are used together with constants to specify both spatial and temporal constraints.

Grammar: governs the overall syntax and structure of the description and specification. Specifically, PDM provides a standard procedure through which the representation of an STP can be formed. The STP can also be specified using the constants and operators defined.

In the following subsections, we first describe the semantics that are defined in PDM, followed by the specification of an STP through the proposed PDM.

4.3.2 Semantics: Constants and Operators

An STP is specified through value assignment to certain sections of the slices. For a prototypical STP, not all the sections are specified. Therefore, we address two issues in pattern specification: 1) which sections are specified and 2) what values are specified for a chosen section. Accordingly, a set of constants and operators are defined in the PDM and applied on the stack of slices to specify an STP.

A set of constant values are proposed to indicate different perceived spatial constraints at a section of the slice for a particular time instance. The dimension of the value set needs to achieve the balance between information fidelity and complexity of the model. The fewer values defined, the less accurate we are to represent spatial constraints, but the model is simpler. The more values defined, the more detailed and precise information is presented, but more complex the model is. In our work,

Table 4.1: Constants defined in *PDM*.

Value	Symbol	Semantics
1		The space represented by the section is occupied by someone moving in the same direction as the observer agent
-1		The space represented by the section is occupied by someone moving in the opposite direction as the observer agent
0		The space represented by the section is unoccupied
-9		The space represented by the section is occupied by static obstacle(s)
*		Do not care whether the space represented by the section is occupied

we define four values 0, 1, -1 and -9 for the current model. The semantics of these constant values are summarized in Table 4.1.

The defined values are capable of reflecting the spatial constraints at specific sections that are relevant to the steering choice of an agent in the model. In terms of spatial occupation, the value of a section indicates whether the section is occupied (non-zero) or available (zero). The value also indicates whether the section is occupied by a static obstacle (-9) or other pedestrians (1 or -1). In terms of the motion features of the perceived pedestrians, the relative moving direction (1 for the same direction and -1 for the opposite direction) and the relative speed (through the change of values of the section along consequent slices) can also be reflected by the values. Such motion features are important to affect steering choices of a pedestrian as will be discussed in detail in the next chapter. To conclude, a value of 0, 1, -1 or -9 is assigned to a particular section of the slices to indicate the perceived spatial constraint at the corresponding area in the environment. For sections of a prototypical STP that are not so relevant to the decision of steering choices, a wildcard character * is assigned.

The constant values defined above reflect various perceived spatial constraints of the situation for a single section of the slices. We now define the operators in the *PDM*. These operators are applied in different *ranges* of sections in both the spatial and temporal dimensions as summarized in Table 4.2.

The first group of operators applies to a single slice to specify spatial constraints:

Range operator is used to specify a particular range in a slice of an STP, where values of the sections are to be specified. A range in this context refers to a

Table 4.2: Operators defined in *PDM*.

Dimension	Operator	Symbol	Usage
Spatial	Range	$[]$	to specify a range of columns in a row of a slice
	Negation	$\neg$	to negate the value of a section or a range of sections
Temporal	Existence	$\rightarrow$	to indicate the existence of certain spatial patterns at a particular slice
	Persistence	$\}$	to indicate the persistence of certain spatial patterns over several consecutive slices

number of consecutive sections in a slice at the same row. A tuple of indices is given as $[P_i, R_i, C_{start}, C_{end}]$ to specify a range, where P_i indicates the index of the slice, R_i indicate the row index of the range, and C_{start} and C_{end} indicate the column indices of the start and the end of the range. An example to demonstrate the range operator is shown in Figure 4.2.

Negation operator is applied on a single or a range of sections in a slice to specify their values as the negated values of a given sequence of values. The negated value for a single section can be either of the other values defined in the constant value set in Table 4.1. The negation of a sequence of values indicates that the given sequence of values does not occur in the selected range. An example to illustrate the use of the negation operator is shown in Figure 4.3.

The other group of operators apply to a single or several consecutive slices in the stack to specify temporal constraints of certain spatial configurations of the situation:

Existence Operator is applied to a particular slice to indicate that the specific spatial constraints exist at that particular time instance in the temporal dimension.

Persistence Operator is applied to a number of consecutive slices in the stack to indicate that the specific spatial constraints need to remain throughout this period of time.

A prototypical STP reflects a pedestrian's perceived situation not only in terms of the spatial constraints, but also the predicted changes of such spatial constraints along time. These two operators are applied to specify such temporal constraints of a prototypical STP. For some steering strategy to be triggered, certain spatial

Figure 4.2: An example of applying the *range operator* to specify a *range* with the tuple $[0,0,3,8]$. For a prototypical STP, the range $[0,0,3,8]$ is not fully specified by the value sequence ‘10’. Two slices are matched if any of the 5 other value sequences (as shown in the figure) can be found in the corresponding range of the comparing concrete STPs. Detailed discussions on the pattern matching process can be found in Section 5.3.2.

constraints need to remain for a period of time. While for others, the existence of certain spatial constraints at a certain moment can trigger the steering strategy. For example, a prototypical STP that triggers the *overtake* steering strategy reflects a situation where the target and the space beside the target remains in front of the observer pedestrian for a period of time. During this period, the pedestrian can catch up with the target. In this case, the persistence operator is applied on the slice representing the perceived spatial constraints (the target and the space beside) with value T to indicate the “persistence” of these spatial constraints for the period T . In another example, the *follow* steering strategy is triggered when a pedestrian perceives no available space in front of her for overtaking, but some others moving slower in the same direction. In this case, the existence operator is applied on the slice representing the perceived spatial constraints to indicate the “existence” of such spatial constraints at the specific moment.

Figure 4.3: An example of applying the *negation operator* to specify the negated value sequence of a *range*: the range with the negated value sequence ‘01’ in a prototypical STP can be matched with its corresponding range in a concrete STP if any of the 15 possible value sequences exists in the corresponding range.

4.3.3 Pattern Specification

With the set of constants and operators defined above, an STP can be specified to reflect the spatial and temporal constraints of a situation perceived by a pedestrian. In the spatial domain, specific values can be assigned to certain sections through *range identification* and *value assignment*. In the temporal domain, requirements on whether certain spatial constraints exist at particular time instance or remain through a predicted period are specified.

4.3.3.1 Methods and Procedures

To specify the spatial constraints, different ranges of a slice are first selected to indicate the areas of interest, where characteristics of a prototypical type of situations are reflected. To identify these ranges, the *visual attention* of pedestrians are considered. The area most attended by a pedestrian likely contains information that is most relevant for her choice on steering strategy selection. This assumption is reasonable to mimic the tendency of proactive pattern searching habits of human’s brain out of the cluttered environment.

There are two types of visual attention models, bottom-up (or stimulus-driven) and top-down (or goal-directed) [21, 100]. The bottom-up attention models generally

integrate features of the environmental elements and allocate the attention to the most salient part of the environment itself [88]. Top-down, on the other hand, covers the goal-directed factors, essentially the task-dependent part of the visual attention. Inspired by such work, the specific ranges in our context can be identified considering the two types of visual attention. First, spatial areas that are commonly attended in the navigation process (e.g., the area in the immediate front of the pedestrians), regardless of tentative steering strategies are first considered. Task-oriented attention is then allocated to different areas that are relevant to the execution process of a tentative steering strategy (e.g., the potential target and the space beside the target for a pedestrian to monitor during the catching up process during overtaking). A *cognitive weight map* can then be synthesized to represent the visual attention of the pedestrian through assigning a numerical value (i.e. between 0 and 1, where 1 indicates the most significant cognitive weight) to each of the sections in the stack of slices as illustrated in Figure 4.4, where the darker the color, the larger cognitive weight value is assigned to a section. The actual cognitive weights can be allocated to different sections of a slice according to the method described in [22]. For general visual attention regardless of a specific steering strategy, the significance of a section is inversely proportional to its relative distance (in terms of the row index) to the agent, its relative deviation (in terms of the column index) from the agent’s vision center, and how much further it is predicted from the current frame (in terms of the frame index). On top of that, sections related to the execution of a particular steering strategy is assumed to be much attended, thus the cognitive weight of these sections need to be adjusted (enhanced) to represent such salient features of these areas. The exact values for the adjustment of weight depend on specific steering strategies.

There are two uses of the cognitive weight map in our approach. First, it can be used to identify most significant ranges in the pattern specification process. Secondly, it is naturally applied in the pattern matching process as the weighted coefficients for integrating and generating the overall similarity of a concrete STP with the partially specified prototypical STP (we address this topic in the next chapter). Through the synthesized cognitive map, a limited number of ranges can be identified in the sections with larger cognitive weights. In the model we have developed, only a small number of ranges are specified in the prototypical STP as shown in Appendix A. The limited number of ranges mimics the limited visual working memory of pedestrians. However, modelers can easily extend to synthesize different cognitive weights for different ranges and to identify different number of ranges as deemed appropriate to model a different experience of a pedestrian.

Figure 4.4: An example of cognitive weight map allocated to dress the attention of pedestrians during their navigation.

A *range operator* is then used on a slice to specify an identified range. The number of sections covered by a range is context dependent, and it is usually set as a ratio out of the total number of columns. Modelers can take into account of certain behavioral habits of a real pedestrian. For example, when defining the “central front” range during an ‘overtaking’ process in our study, the number of sections is set to 60% of the total sections in a row. This is based on the observation that a pedestrian seldom deviates more than 60° in their movement (Thus, the central range to consider detouring for overtaking is $120^\circ/180^\circ \approx 0.6$). Theoretically, such an observation is described by the *angular minimization rule*, which is reported in the pedestrian study [37]. Through this step, several ranges of an STP are identified. The set of ranges reflect the spatial areas, where the visual attention of a pedestrian is normally located. Spatial constraints observed from such areas affect the pedestrian’s choice of steering strategies in the situation.

In the second step, each range as identified in the first step is assigned with values to indicate the spatial constraints, which contribute to trigger the selection of a particular steering strategy. Different steering strategies require different spatio-temporal constraints, thus different values are specified in the identified ranges. For example, the value sequence “01” is specified in the “central front” range to trigger the “overtake” steering strategy, while “1-0” is defined to trigger the “follow” steering strategy. Note from the example that the *negation operator* is applied to specify a value (or value sequence) that is deemed not to exist in a range. The remaining

sections beyond the identified ranges are filled with the arbitrary value *. Through these two steps, a slice can be specified.

A specified slice is then assigned with temporal operators corresponding to the execution processes of different steering strategies. Either an *existence* or *persistence* operator is used to indicate such temporal constraints. In our model, we have specified several prototypical STPs corresponding to the three common steering strategies based on pedestrian studies and our observations on the characteristics of the situations. The details of the specification are illustrated in Appendix A.

4.3.3.2 An Example for STP Specification

Let us use a simple example to demonstrate the pattern specification for a prototypical STP corresponding to the *overtake* steering strategy. One could think of a typical situation as shown in Figure 4.5(a), where *a pedestrian perceives blockage in front of her caused by some slow movers in the same direction, and there is space beside the slow movers for her to catch up and pass ahead*. Such a situation can trigger the *overtake* steering strategy.

Based on the situation description above, we examine such a typical situation through the empirical execution process of the associated steering strategy. The overtake steering strategy can be executed through two phases along time. Thus, two different slices with corresponding spatial constraints are specified corresponding to these phases as shown in Figure 4.5(a). In the first phase, the target to overtake together with the space beside it needs to persist for a period of time T_0 , during which the pedestrian can *catch-up* with the target. To reflect such a spatial constraint observed in this phase, a value sequence “01” is specified in the range at the middle of the slice p_0 as shown in Figure 4.5(b). Once the pedestrian has caught up with the target, she needs to *pass-ahead* of the target to complete the overtaking process in the second phase. In this phase, some space needs to exist in front of the pedestrian, represented by the value “0” at slice p_1 in Figure 4.5(b). The parameter T_0 in this example illustrates the temporal constraints to consider in specifying a prototypical STP. In simulations, the value of the parameter is set according to the relative velocities of the observer and target agents, which is demonstrated in Figure 4.6, where R_1 is the inner attention range of the agent; r is the radius of the observing agent including its personal space factor. V_t is the current velocity of the target to overtake; V_o is the preferred velocity of the observing agent to execute the *overtake* steering strategy.

(a) A typical situation where pedestrians are likely to overtake. The overtaking process can be executed through *catch-up* (figure on the left) and *pass-ahead* (figure on the right)

(b) Pattern specification through two steps

Figure 4.5: Pattern specification for a prototypical STP corresponding to the *overtake* steering strategy.

To this end, PDM allows modelers to specify an STP by filling the slices with a set of constant values at different ranges. Together with corresponding temporal constraints, the spatial and temporal configuration of a situation is characterized. Such a situation associates with particular steering strategies that are usually triggered under the situation. PDM provides a standard way for pattern specification, especially for the purpose of prototypical STP design in this thesis to mimic different steering experiences of pedestrians.

4.4 Summary

In this chapter, we have first discussed the general patterns that pervade daily life. We further examined the habitual preference of using patterns in human brains. Motivated by the wide use of patterns, *spatio-temporal patterns* are proposed to represent

Figure 4.6: Calculation of the temporal constraint in defining the prototypical STP to trigger the *overtake* steering strategy.

the implicit criteria, on which pedestrians rely for efficient decisions on different steering strategies. An STP is used to reflect the visually perceived spatial constraints in the situation and the projected dynamic change of such constraints along a predicted period of time. The comprehensive information contained in the STP represents the situation as a whole.

In the second part of this chapter, we have proposed the Pattern Description Method (PDM) to allow modelers to specify an STP. Through analogizing to a language that consists of semantics and grammar, we described the constants and operators defined in PDM. By applying these constant values and operators, an STP can be first separated into different ranges to address different cognitive attention of a pedestrian in perceiving a situation. A limited number of ranges are identified to represent the most likely attended area during their steering process. Value sequences are then assigned to the identified ranges representing the corresponding perceived spatial constraints in accordance of the execution phases of a steering strategy. A steering strategy may be executed through multiple phases, thus different spatial constraints are specified for each of the execution phases with temporal constraints and

cohesion among these phases.

The definition, representation and specification of an STP will be applied in constructing a model to simulate the steering behaviors of pedestrians through the proposed pattern-based approach in the next chapter.

Chapter 5

A Pattern-Based Steering Model

In this chapter, we propose a Pattern-Based Steering (PBS) model for pedestrian simulation (particularly focusing on the local path determination layer in the motion modeling structure) based on the theoretical basis and concept of spatio-temporal patterns (STP) that were discussed in the previous chapters. The PBS model is developed based on a cognitive architecture following the *perceive-decide-act* paradigm from the ABM approach. Under this architecture, we adopt a pattern-based approach to address the three key components in the cognitive processes: the perception, decision and action system and discuss how the concept of STPs are embedded in the design to realistically mimic the cognitive process of a pedestrian in real life situations.

5.1 Overview of PBS: The Architecture

We believe that realistic strategic steering behaviors can be generated by imitating the cognitive processes of pedestrians regarding how they *perceive* the situation, *decide* on adopting different steering strategies and eventually *act* in their movement. The overall cognitive process is modeled as a continuous process following the *perceive-decide-act* paradigm as shown in Figure 5.1.

In the *perceiving* process, an agent first senses the current situation, and the raw sensed data are further processed by the attention system. The agent then generates its comprehension of the overall spatial constraints of the situation from the sensed information. In addition to the spatial constraints, prediction is involved to consider the temporal constraints, or the change of spatial configuration along time. Through this process, a concrete STP ($\mathbb{A}$) is formed to represent its comprehensive perception of the situation in both spatial and temporal domains, which in turn influences its steering strategy choices through pattern matching as specified in the *deciding* process.

In the *deciding* process, the agent matches $\mathbb{A}$ against a set of prototypical STPs ($\mathbb{B}_1 \sim \mathbb{B}_n$) stored in its *experience base*. The experience base is essentially a model of

Figure 5.1: Cognitive architecture of the PBS model.

the working memory of a pedestrian, storing a limited set of steering strategies that are commonly applicable to the current scenario. We do not fully understand how steering strategies are retrieved from the long term memory, but in this thesis, this higher level cognitive process is modeled as a pattern matching process between a concrete STP and the set of prototypical STPs. An experience base consists of a set of *experience instances*. An experience instance E_i is defined as a tuple $\langle \mathbb{B}_i, S_i, ac_i \rangle$ associating a prototypical STP $\mathbb{B}_i$, the corresponding steering strategy S_i , and the procedural execution ac_i for the steering strategy. The matched prototypical STP, $\mathbb{B}_i$ serves as the cue to retrieve the associated steering strategy S_i . The complex cognitive processes involved in steering decision making are essentially transformed to a pattern-matching process between the perceived concrete STP and the internally stored prototypical STPs.

Once a steering strategy S_i is selected, the associated procedural execution ac_i (e.g., how to choose a target to overtake, whether to overtake the target from left/right side) is retrieved from the experience instance E_i and is applied to generate a course of actions in the *acting* process. Such execution procedures serve as a benchmark to model the execution process of a steering strategy S_i in terms of a sequence of actions. For instance, the execution of “overtake” steering strategy can be further divided into *catch-up* and *pass-ahead* phases as previously discussed, where different preferred velocities of the agent may be specified accordingly. The execution procedures may be applied in the current situation with proper adaptation to accommodate the unique spatio-temporal configuration of the current situation. The adaptation can be handled through various motion control mechanisms such as the Reciprocal Velocity Obstacle (RVO) [219, 221] and social force approaches [69, 92] at the locomotive level, which generates the adjusted strategic motion as discussed in Section 3.2 (see Figure 3.1).

At the abstract framework level, this architecture is highly consistent with the RPD model [104] as reviewed in Chapter 2, which reflects naturalistic decision-making [247] processes of humans, addressing the importance of *experience*. In the PBS model, each experience instance consists of a prototypical STP (*cues* in the RPD term) and a steering strategy. A steering strategy is specified by the procedural instructions on its execution process in the corresponding situation. Goals, expectations and actions in the RPD terms are reflected by parts of the procedural instructions. An agent has two states, one in which a steering strategy is selected and one in which no steering strategy is currently selected. When no steering strategy is selected, a steering strategy is to be selected through a pattern-matching process between the concrete

STP (currently perceived) and prototypical STPs. If a strategy is selected through the matching process, matching is no longer necessary in the subsequent steps. The selected steering strategy is then executed according to the procedural instructions until such time as the expectancies are violated or the goals have been achieved (again consistent with RPD). If no steering strategy is selected, the agent performs either *non-strategic movement* or *instinctive reactions* according to the matching process as discussed in Chapter 3. In either case, the agent will have to re-assess the situation and perform the pattern-matching again in the next simulation step. Iterations of situation assessment, steering strategy selection (when necessary) and execution are performed by an agent in the simulation. An important feature of this architecture is the use of violation-checks during the strategy execution process as shown in Figure 5.1. Perception formation and the pattern-matching process only occurs when a new steering strategy needs to be made due to the violation of the current strategy, completion of the current strategy or the achievement of the current goal. Such a feature gives a distinct benefit when compared to the direct motion control on the locomotive level, where the environment is assessed at each time step in the simulation. We argue this may reflect the naturalistic decision-making process of humans as suggested in the RPD model. In real life, people are likely to choose a course of actions (execution of a steering strategy) and continue with that course until they find the current situation is no longer consistent with what they expect. As a result, people are observed to change their steering choices only infrequently.

In the following sections, we depict each of the three main components *perceive*, *decide* and *act* of the PBS model in detail.

5.2 Perceive: Situation Assessment

It is a critical research issue in this work to understand how pedestrians assess and perceive the situation during their movement. We address the perception system of the PBS model in this section.

In *human factor* studies [40–43], the term *situation awareness* is widely used to describe the state, where a human understands the situation and makes use of such information to inform its actions. In the work [42], Endsley formally defined the term and it has been widely applied. According to this definition, there are three levels of situation awareness: *a person’s perception of environmental elements within a volume of time and space; the comprehension of their meaning; and the projection of their status in the near future*. In the PBS model, an agent’s comprehensive perception

of the situation is represented by a concrete STP, which reflects the perceived constraints of the situation both in the spatial and temporal domains. In these regards, a concrete STP is similar to the situation awareness both in terms of semantics and its function as the subject's decision-making criteria to select appropriate steering strategies. Similarly, an agent can form its concrete STP from the situation through three steps as shown in Figure 5.2. Such a pattern formation process is also referred to as the *situation assessment* process in this work.

Figure 5.2: Concrete STP formation is modeled through three steps in the situation assessment process.

5.2.1 Step One: Sense the Environmental *Elements*

During navigation, a pedestrian continuously senses the environment through various sensory inputs (e.g., vision, audition, etc.). In the PBS model, we mainly consider the *visual* information because the steering choices of the pedestrian is mainly affected by the visually perceived spatial and temporal constraints of the environment. In order to mimic the continuous perceived space of the situation, we have adopted a *radial intersection scanning* method to model the vision system of an agent as shown in Figure 5.3(a).

The vision system consists of a *vision center*, a *vision range*, a *vision angle*, two *vision boundaries* and multiple *vision radials*. The *field of vision* is formed as the bounded region within the vision range and vision boundaries and it can be blocked by other objects in the environment such as walls as indicated in Figure 5.3(a). These terms are defined as follows:

- **Vision radial:** models the sight line of a pedestrian along a specific direction.

Figure 5.3: Vision system and agent measurement.

- **Vision center:** represents the central sight line of a pedestrian, which in most cases aligns with the moving direction pointing from the current position to the destination.
- **Vision range:** indicates how far in front of a pedestrian that she visually senses and responses to the visual information.¹
- **Vision boundary:** defines the limit of peripheral vision.
- **Vision angle:** indicates how wide a pedestrian can visually sense the environment. It is the angle between the two vision boundaries.

Through the vision system, a sensed agent Agt_i can be measured through a set of spatial and motion features relative to the observing agent (Agt_0) as shown in Figure 5.3(b). In terms of spatial features of Agt_i , its *relative position* in the vision of Agt_0 can be precisely measured as a vector $\vec{P}_{i0}$ pointing from Agt_0 to Agt_i ; its *size* could be measured through its diameter d and its *relative velocity* $\vec{V}_{i0}$ is used to indicate its motion feature. Traditional motion planning methods [69, 169, 219] make use of these parameters to calculate the velocity of Agt_0 to ensure collision-free motion. Each of the sensed agents is processed in a sequential and accumulative manner to exclude velocities that will lead to collisions.

¹People can see further, up to kilometers away. However, they react only to nearby objects. Therefore, this range is not the actual limit of vision, but the limit of their response to visual information.

In real life situations, however, pedestrians hardly sense and conduct accurate mathematical calculations against each individual objects in the environment sequentially. Instead, they, most likely, sense and group [45] multiple objects in a parallel manner to assess the overall spatial constraints of the situation as a whole. Researchers in the visual attention research area call this the “gist” of the scene [21, 194]. For example, they tend to perceive a “group” of people instead of individuals. They also seem to measure the environment naturally through fuzzy and qualitative terms such as “far”, “normal” or “near” rather than quantitative measurement in terms of meters. To model such sensing habits of pedestrians, we propose that agents sense the environment through *elements* instead of individual objects in the PBS model. The perceived *elements* of an environment mainly consist of *static obstacles*, *dynamic obstacles* and the *space* between different obstacles falling into different regions of the field of vision. Each element may contain a single or multiple obstacles through grouping.

Grouping is a common cognitive practice for people to handle a large amount of information. People are capable of processing a limited number of (i.e., 7 ± 2) information chunks in their working memory at one time [67, 130]. In the vision-guided tasks such as navigation, an individual chunk of information obtained through visual perception may consist of multiple people perceived as a group. In this work, grouping is based on the similarity of individual agent’s positions and moving direction. Only agents with similar moving directions and close to each other in the field of vision of the observer, are sensed as a single element. Based on these two criteria, agents are perceptually grouped. Through sensing by elements, the environment is perceived as consisting of elements $O_{1,2}$, $D_{1 \sim 3}$ and $Sp_{1,2}$ in the example as demonstrated in Figure 5.4(a).

Each element can be assessed through its spatial and motion (only for elements consisting of dynamic obstacles) features. Two types of spatial features are generally considered: *relative position* and *perceived size* of the element. These features can be precisely calculated through the parameters $\theta_{1,2}$, d and w as shown in Figure 5.4(b). However, such parameters represent the sensed information rather than the formed perception of the situation. The perceived information about the spatial and temporal configuration of the situation is further formed based on the features of different elements as will be discussed shortly.

Figure 5.4: Elements of the environment in a situation.

5.2.2 Step Two: Comprehension of Spatial Constraints

Through sensing, spatial and motion features of each individual element in the situation can be captured by an agent. In this step, the agent comprehends such information and forms its perception on the spatial configuration of the current situation. By comprehending, an agent cognitively processes and aggregates the spatial features of multiple elements to estimate the perceived spatial constraints of the situation that impact on its choice of steering strategies. As discussed in Chapter 4, the comprehended spatial constraints are represented in the form of a *slice* with values indicating the spatial features of the situation at the corresponding spatial region. To correlate different spatial areas attended by the agent with the corresponding *sections* in a slice, we propose to divide an agent's field of vision into different partitions through the attention system as shown in Figure 5.5.

Terms we use in describing the model related to the attention system is listed as below:

- **Overall Attention Area:** represents the whole spatial area, within which the sensed spatial information is relevant to form the concrete STP. In the current model, this is equal to the field of vision.
- **Attention Range:** represents the distance from the agent to form different attention zones.

Figure 5.5: Attention system: modeled through radial scanning intersection.

- **Attention Zone:** represents the specific spatial area within a attention range, where specific cognitive weight (attention) is allocated.
- **Attention Column:** represents each of the distinctive spatial areas along a direction that is specified by two consecutive vision radials.
- **Attention Section:** represents each of the mutually separated spatial areas through the intersection of different attention ranges and vision radials.

Through the proposed attention system, the *overall attention area* is divided into a number of *attention columns* laterally and *attention ranges* longitudinally. In the example as shown in Figure 5.5, there are 51 *attention sections* formed. In the simulation, the number of attention columns depends on the the value of attention ranges and the sensed size of the agent (including the personal space factor [200, 216]). Such a partition of space correlates to the representation of an STP, where an attention range, attention column and attention section in the attention system corresponds to a *row*, *column* and *section* of a *slice* in the STP representation as shown in Figure 5.6.

Each perceived element of the environment occupies one or more attention sections. Spatial features of an element can then be estimated to represent the spatial constraints through its occupation of particular attention sections. The relative position of a perceived element is approximated by the position of the attention sections in the overall attention zone. The perceived size of an element is approximated as its spatial span over the number of attention sections that it occupies. Note that there is a difference between the physical occupation of an element in the space and

Figure 5.6: Perceived spatial constraints in the attention system and the formed *slice* in an STP.

the perceived occupation in the respective attention sections. We include a personal space factor of an element to measure the spatial occupation. The first attention range (R_0) is set dynamically in simulation according to the perceived local density or the distance between the nearest neighbor in the vision range and itself. R_0 is set such that only one agent including its personal space is perceived as fully occupying one attention column at the boundary of the attention range. The length of further attention ranges are set to increase exponentially (i.e., $R_0:R_1:R_2 = 1:2:4$). With these settings, the perceived sizes of the same element are different within different attention zones. If the element is closer to the observing agent, its perceived size is larger and the number of formed attention columns is smaller. Such approximations naturally reflect the *attenuation theory* [211] of visual attention in the way that a nearby agent will contribute more to the comprehensive perception of the spatial constraint. We also include some constraints on the attention ranges such that the first ('near') attention range is neither too short nor long in extremely dense or sparse scenarios. The minimal value is set such that at least three attention columns are formed. Under such a condition, the observing agent needs to deviate around 60° (assuming the vision angle is 180°) in order to avoid another agent in the middle, which is rarely observed in real life situation. While the maximal value is set to 3.5 m to avoid forming a large number of attention columns unnecessarily in the extremely sparse scenario, where even the nearest agent is still far away.

As mentioned, agents of similar position and moving directions are grouped as a single element in the sensing step. Through the attention system, we say that two agents are similar in position if they are located in the same attention sections.

Their moving directions are qualitatively categorized into two groups “same” and “opposite”. In the model, the direction can be deduced through the angular difference between the observing agent’s preferred velocity and the observed agent’s current velocity according to certain simple fuzzy rules (i.e., if the difference is larger than a threshold value, say 90° , then the relative direction is set to “same”). In cases where multiple agents fill the same attention section at further attention zones, the nearest agent to the observing agent is considered as the representative agent of that attention section. This is because the vision radials forming that attention column may be obscured by the nearer agent. Through this comprehension, the motion feature of an element possibly consisting of multiple agents can be estimated through the motion features of the representative agent.

A slice is used to represent the perceived spatial constraints of the situation in an STP. The value of a section in a slice is assigned according to the constants defined under the Pattern Description Method (PDM) as discussed in Chapter 4. To summarize for a quick review: if the section is unoccupied, then value 0 is set for this section; if it is occupied by static obstacles, then it is set to -9; if the section is occupied by dynamic obstacles (agents), the value is set to either 1 or -1 depending on whether the representative agent of the element is perceived as moving in the same or opposite direction as the observing agent. Eventually, either 0, 1, -1 or -9 is assigned to each of the section in a slice to represent the comprehensive spatial constraints as perceived by the observing agent. For example, a slice is generated as shown in Figure 5.6(b) corresponding to the situation as shown in Figure 5.6(a).

At this step of situation assessment, all the obstacles (both static and dynamic) and the space between them in an agent’s field of vision are understood to form the perceived spatial constraints of the situation.

5.2.3 Step Three: Projection of Temporal Constraints

Besides assessing the spatial constraints of the situation for the current moment, pedestrians form a comprehensive perception of the situation by taking into account the dynamic change of spatial configurations due to the continuous movement of both themselves and other surrounding pedestrians. During navigation in real life situations, pedestrians proactively plan in advance by adopting steering strategies to avoid collisions with other pedestrians. Since the situation is dynamic, emerging from the movement of many individuals in the crowd, pedestrians are assumed to make short term prediction of the spatial configuration in order to make effective steering choices

 Figure 5.7: Spatio-temporal configuration of the situation in a stack of *slices*.

in advance. We model this capability of pedestrians to form the perceived temporal constraints of the situation through a prediction function. Prediction currently is based on a *linear dead reckoning* method² to deduce the spatial features of each sensed agent along the predicted period of time T . In the model, T is set as $\min(3s, ttc)$, where ttc indicates the time to collision calculated using the current velocities of the observing agent and the nearest agent that is in the immediate front (i.e., the agent that occupies the section at the first row and the middle column in the formed STP). $3s$ is the default prediction time we set in the model. Similar default value is used in previous models that based on linear prediction methods [97, 155], which suggests that the prediction longer than 3 seconds results in inconsistent and less useful predicted status of the situation in their decisions. Through this prediction process, the location of a perceived agent within the attention zone can be calculated based on their current position and velocity relative to the observing agent. The spatial constraints are then estimated through the same process as described in the second step. A new slice is formed to represent the predicted spatial constraints of the situation for that particular moment in prediction. The generated stack of slices represents the perceived spatial constraints for both the current and the predicted time as shown in Figure 5.7. To this end, a concrete STP, in the form of a stack of slices, is formed at the end of the situation assessment process. The three-step approach to modeling the perception process brings several benefits:

²In principle, this could be changed to some other forms of prediction.

- Both spatial and temporal information is implicitly embedded into a single form, a concrete STP, which facilitates the pattern-matching process.
- Intuitive modeling of the visual perception of pedestrians in the way that information is processed in a parallel and fuzzy manner to achieve good trade-off between estimation and comprehensiveness.
- Perspectives of the vision and attention are reflected realistically through the egocentric design in the situation assessment process.

5.3 Decide: Pattern Matching

5.3.1 Overview

As discussed in Chapter 3, it is assumed that pedestrians proactively apply a limited number of steering strategies to avoid collisions efficiently. The scheduling, selection and execution of these steering strategies are determined through a pattern-matching process between the currently perceived *concrete* STP and the predefined *prototypical* STPs. The decision-making process of an agent is eventually transformed to a pattern-matching process, which is described in this section.

In general, pattern-matching is the act of checking for the presence of the constituents of a given pattern in the comparing pattern. At a decision point, an agent assesses the situation and forms a concrete STP, denoted as a three-dimensional matrix $\mathbb{A}_{RC}^T$, where R indicates the number of attention zones, C indicates the number of attention columns (see Figure 5.5), and T denotes the length of prediction in number of frames. $\mathbb{A}_{RC}^T$ is then matched against each of the pre-defined prototypical STPs denoted as $\mathbb{B}_{R'C'}^{T'}$.

The sequence of matching the set of prototypical STPs of an agent is an important aspect of the decision-making process. In general, the sequence is determined by the number of ranges with specific values defined in the prototypical STP. In our model, the prototypical STPs are checked in the sequence corresponding to the “overtake”, “follow” and “side-avoid” steering strategy for the following reasons. First, it is noted that more ranges are defined and thus to be matched for the prototypical STP associated with “overtake” than “follow” (see Figure A.1 and Figure A.2). Thus more spatial and temporal constraints are required to be matched to trigger the “overtake” than the “follow” steering strategy. Secondly, the chances of “side-avoid” could be potentially reduced by applying the other two steering strategies. For example, by

following someone in front, a pedestrian may not need to “side-avoid” with others coming towards him deliberately. This could be a possible reason to explain the lane-formation phenomenon that is commonly seen to emerge in pedestrians’ navigational behaviors in real-life situations.

Several spatial and temporal constraints are usually defined in a prototypical STP, thus to be matched as the constituents of the STP. From the modeling perspective, a steering strategy can be executed through several phases (e.g., the *catch up*, *pass ahead* phases for “overtake”), thus different spatial and temporal constraints are specified in the respective prototypical STP according to these phases. We represent the overall prototypical STP as:

$$\mathbb{B}_{R'C'}^{T'} = \langle \langle \mathbf{b}^0, t_0 \rangle, \langle \mathbf{b}^1, t_1 \rangle, \dots \rangle$$

where $\mathbf{b}^i$ indicates the slice containing the specific spatial constraints for the i^{th} phase of the procedural instruction on the steering strategy execution process associated with $\mathbb{B}_{R'C'}^{T'}$; t_i specifies the maximum number of slices in $\mathbb{A}_{RC}^T$ to be (persistently) matched with $\mathbf{b}^i$ according to the temporal constraints specified in $\mathbb{B}_{R'C'}^{T'}$. If an existence operator is applied to slice $\mathbf{b}^i$ in the prototypical STP specification, $t_i = 1$, indicating only one slice in $\mathbb{A}_{RC}^T$ needs to be matched with $\mathbf{b}^i$.

The overall matching process $\mathbb{A}_{RC}^T$ and $\mathbb{B}_{R'C'}^{T'}$ reflects the fact that both the spatial and temporal constraints exhibited in the stored prototypical STP are present in the current situation. Thus, we define the match along both the spatial and temporal dimensions. In the spatial dimension, *slice matching* is conducted between corresponding slices in $\mathbb{A}_{RC}^T$ and $\mathbb{B}_{R'C'}^{T'}$ to indicate how similar the perceived spatial constraints of the current situation is to a prototypical situation. In the temporal dimension, *stack matching* is carried out along the stack to indicate the match of temporal constraints of the specified spatial patterns corresponding to a particular phase of the strategy execution process.

A perfect match between $\mathbb{A}_{RC}^T$ and $\mathbb{B}_{R'C'}^{T'}$ is achieved if all the slices $\mathbf{b}^i$ specified in $\mathbb{B}_{R'C'}^{T'}$ are matched with slices in $\mathbb{A}_{RC}^T$ for t_i respectively. In many situations, such a perfect match is rarely achieved. Nevertheless, a steering strategy can be triggered upon a partial match. Partial matching is even preferred to mimic the different experiences of pedestrians to apply certain steering strategies when perceiving the same situation. Personal traits are considered in the model to allow partial matching to trigger a particular steering strategy at different degrees of matching. Specifically, the *commitment level* on the steering choices of a pedestrian determines the total number of slices to be matched (or the ratio of the matched slices out of the total

number of slices T in $\mathbb{A}_{RC}^T$) in order to achieve a match between two STPs. We include the commitment level as a parameter to model the personal traits of individual agents in the PBS model.

We discuss the *slice matching* and *stack matching* processes and how they contribute to the overall matching result between a concrete and a prototypical STP in the following subsections.

5.3.2 Slice Matching (Spatial Patterns)

In terms of the match in the spatial dimension, *slice matching* between slices $\mathbf{a}$ and $\mathbf{b}$ from $\mathbb{A}_{RC}^T$ and $\mathbb{B}_{RC'}^{T'}$ is conducted. The match of the two slices is aggregated through the comparison results of the comprising ranges in the slices. For each of the specified ranges f_i in slice $\mathbf{b}$, a value sequence is specified and noted as:

$$X_i = (x_1, x_2, \dots, x_w), w \text{ is the horizontal spatial span of } f_i$$

Since the attention ranges (R_1, R_2, R_3) are set dynamically according to the local density, the number of attention columns vary across different situations. Thus the size of a concrete STP changes dynamically. As a prototypical STP is specified with relative ratio on ranges (e.g. a range which occupies 50% of the total columns in the middle) before the simulation, the size of the prototypical STP needs to be set according to the size of the concrete STP in the simulation. For this purpose, we first define the *corresponding range* in the slice of the concrete STP based on the relative location of the range to the central column of the first row. A range's spatial span is normalized as a ratio between the number of specified columns and the total number of columns in the slice. Such a ratio is also capable of representing certain qualitative cognitive terms such as the "central" area in a pedestrian's perception. We quantify a range f_i in a slice of a prototypical STP denoted through three quantifiers:

$$f_i = \left(d, \frac{l}{C}, \frac{w}{C} \right)$$

where d is the vertical distance (in terms of the index of attention ranges R_i), l is the distance from central column (in case there are two when the total number of columns is even), w is the horizontal spatial span of the range, and C is the total number of columns in the prototypical STP. The corresponding range f'_i in a slice of the concrete STP can then be deduced through:

$$f'_i = \left(d, \frac{l'}{C'}, \frac{w'}{C'} \right) \tag{5.1}$$

Figure 5.8: Corresponding range deduction in slice matching: the two corresponding ranges f_1' and f_2' in **a** are deduced from ranges f_1 and f_2 in **b**. Both represent the same area of interest in the space from the egocentric perspective of the agent.

where $l' = \lceil \frac{lC'}{C} \rceil$, $w' = \lceil \frac{wC'}{C} \rceil$, $\lceil \cdot \rceil$ represents a ceiling function, C' is the number of columns in the slice of the concrete STP.

Due to the symmetric features of pedestrians' vision, a *symmetric range* f_i'' of f_i' is also considered in the slice matching for particular steering strategies. f_i'' is generated through a horizontal flipping operation of f_i' on slice **a** with the central column as the flipping axis. An example for corresponding range deduction from the given prototypical STP slice is illustrated in Figure 5.8.

Once the corresponding ranges are identified in the slice **a**, the next step is to check whether the specific value sequence X_i in f_i exists in f_i' . Even though this can be achieved easily through simple searching algorithms, two issues should be noted. First, the actual location of X_i in f_i' can vary within the range according to the definition of the *range operator* in the PDM. Secondly, for the symmetric ranges f_i'' ,

the sequence of values $\tilde{X}_i$ to be checked are the inverse value sequence of X_i . For example, for $X_i (= 01)$ in f_i of slice **b**, $X_i (= 01)$ will be checked in f_i' and $\tilde{X}_i (= 10)$ will be checked in f_i'' .

The value sequence X_i in a range of slice **b** is then matched with the values in the *corresponding range* f_i' and the *symmetric range* f_i'' in slice **a**. The similarity F_i between the comparing ranges defines how similar the spatial constraints are observed from the two ranges. It is measured as a step function:

$$F_i = \begin{cases} 1, & X_i \text{ exists in } f_i' \text{ or } \tilde{X}_i \text{ exists in } f_i''; \\ 0, & \text{otherwise.} \end{cases} \quad (5.2)$$

Assume there are K ranges f_i , where $1 \leq i \leq K$, specified in a prototypical STP. We define the aggregated similarity (or the overall degree of match) for all the specified ranges as a vector F :

$$F = \{F_1, F_2, \dots, F_K\} \quad (5.3)$$

To aggregate the matching results of each individual ranges, the cognitive weight map is applied to weigh and sum the resultant vector F of the slice matching. As mentioned in Chapter 4, a cognitive weight map can be imposed by the modeler to mimic the use of attention in the range identification process. Each section in the slice is assigned a value between 0 and 1 to indicate how significant the spatial area represented by this section is in forming the comprehensive visual perception of the situation. The overall match score γ between two compared slices can be calculated as

$$\gamma = \sum_{i=1}^K \omega_i F_i, \quad (5.4)$$

where ω_i indicates the weight of the range f_i , which is set as the maximum cognitive weight value of the sections within the range since a range may span over multiple sections and the specified value sequence can vary within the range. K is the total number of ranges specified in the slice **b** of the prototypical STP. Since the value of K varies for different steering strategies and slices, the normalized match score is calculated as:

$$\gamma_{norm} = \frac{\gamma}{\sum_{i=1}^K \omega_i}. \quad (5.5)$$

We say that the two slices are matched if γ_{norm} is larger than a threshold of match score $\gamma_{threshold}$ to allow for partial match between the slices compared. Together with the unevenly distributed cognitive weights for different sections in a slice, such partial matching between slices ensures our approach is capable of handling a certain degree of uncertainty in the situation. From this perspective, $\gamma_{threshold}$ determines the degree of freedom in the uncertainty handling for slice matching in the model. The default value of $\gamma_{threshold}$ is set to 0.8 as a limited number of ranges are specified in the prototypical STPs we have designed in this model.

5.3.3 Stack Matching (Temporal Patterns)

As discussed in Chapter 4, in the specification process of a prototypical STP, for each specified slice b^i , a temporal constraints t_i is assigned. To match two STPs in the temporal dimension, different number of slices are required to match with the prototypical STP. We refer to this process of matching a total number of T slices as the *stack matching*.

In order to match two STPs ($\mathbb{A}_{RC}^T$ and $\mathbb{B}_{R'C'}^{T'}$), we start slice matching between the first slice in each STP, a^0 and b^0 . The subsequent pairs of compared slices are taken from $\mathbb{A}_{RC}^T$ and $\mathbb{B}_{R'C'}^{T'}$ determined by the temporal constraint t_i . A slice b^i is compared for t_i slices taken from $\mathbb{A}_{RC}^T$ in sequence. This process continues until such time as the $\mathbb{A}_{RC}^T$ fails or succeeds to match with certain number of slices of $\mathbb{B}_{R'C'}^{T'}$.

The number of slice matches to define the STP match is subjective to individual steering strategy and the personal traits of pedestrians in their planning ability on steering strategies. For different steering strategies, different temporal constraints on certain perceived spatial patterns are specified in their associated prototypical STPs. For example, the spatial pattern that allows one to overtake others needs to be persistent for certain slices in order to trigger the “overtake” steering strategy, while “side-avoid” can be triggered once the spatial pattern is detected to allow “side-avoid”. In addition, pedestrians with different personal traits tend to trigger a steering strategy upon different levels of pattern matching. People who we describe as “cautious” or “far-sighted” (e.g. who can predict the situation better in the future) tend to keep high commitment to their plan (i.e., a selected steering strategy) once they have made a decision. While for some others such as children, they may not be able to forecast far ahead from the current situation, and thus tend to apply certain steering strategy immediately after detecting certain spatial patterns. However, the execution process of their choice of steering strategy may be interrupted more often than those who are

more committed. To capture this difference caused by personal traits, we introduce a *commitment level* parameter δ for an agent. δ represents the ratio of the number of slices that are required to be matched between the concrete and prototypical STPs, in order to achieve the overall STP match. The number of slices required to be matched is thus $\delta \cdot T$, where T is the total number of slices formed in the perceived concrete STP, $\mathbb{A}_{RC}^T$.

In summary, the choice of steering strategies at a decision point is based on the result of the matching between the perceived concrete STP formed dynamically at run-time and the predefined prototypical STPs that mimic the experience instances of pedestrians. Two slices are matched if the normalized weighted sum of similarities of all the specific ranges of the slices meets certain threshold value. To determine the required number of slices to be matched along the stack, personal traits, in particular, the commitment level of an agent is used.

5.4 Act: Steering Strategy Execution

5.4.1 Overview

As discussed in Chapter 3, we propose to model the navigational behaviors of pedestrians more realistically through a tri-layered motion structure, which consists of path planning, local path determination and locomotion. The focus of this work is in the middle layer, where pedestrians proactively apply simple steering strategies to avoid collisions efficiently. The execution process of these steering strategies forms the *act* component of the PBS model.

Through the pattern-matching process as discussed in the previous section, a particular steering strategy is selected at a decision point and will be executed in a sequence of actions. A *preferred velocity*, V_p^i is generated (refer to Figure 3.1) as the procedural instruction for the agent to execute the strategy through the i^{th} phase.

At the locomotion level, the agent takes the generated preferred velocity as the input for the current phase of the strategy execution and calculates the *actual velocity* of the agent for this time frame. In this model, we have implemented the locomotive mechanism according to the RVO2 library [221]. Theoretically, any locomotive mechanism (such as the social-force model [69]) that takes in a preferred velocity and outputs an actual velocity for collision-avoidance purposes can be substituted in our model. RVO2 was chosen for its computational efficiency and good collision avoidance performance [222]. The locomotive mechanism is used in our model for two purposes:

first, to check the violation of the current steering strategy, where an agent may not resolve potential collisions by adopting the steering strategy. Secondly, to ensure the collision-free motion of agents when there is no steering strategy selected due to lack of a pattern match. In both cases, the locomotive motion control mechanism takes over the strategic steering behaviors to mimic the instinctive reactions for imminent collision avoidance.

We set the *time horizon* τ (a key parameter in RVO2) to be the same value as the frame rate of our simulation for two major reasons³. First, such a setting minimizes the interference of the locomotive mechanism on the strategic choice planning. The motion control mechanism only steps in at the last frame to resolve potential collisions when there is no steering strategy or the steering strategy fails to avoid collisions. Second, such a setting provides a consistent model configuration for fair model comparisons in the evaluation process (see Chapter 7). Specifically in this model, we have developed three commonly observed steering strategies as ‘follow’, ‘overtake’ and ‘side-avoid’ that pedestrians adopt in real life situations. We formally define each of the steering strategies and discuss their empirical execution processes in the following subsections.

5.4.2 Follow

‘Following’ is a commonly observed behavior of pedestrians in real life situations, particularly in crowded scenarios. Macroscopic phenomena such as lane formation can emerge from a relatively large number of individuals adopting ‘following’ behaviors. The notion ‘follow’ we take in this thesis as an appropriate steering strategy refers to:

An active cognitive process and the subsequential sequence of actions, where an individual decides consciously to remain behind someone or some group moving in the same general direction.

The adoption of the *follow* steering strategy may be because the surrounding space is too crowded to make a reasonable ‘overtake’, or because people feel that by following others they will reduce their effort to avoid collisions with the oncoming pedestrians. In the case where an individual passively walks behind another without any cognitive awareness of the following process, we do not consider it as a steering strategy.

³Theoretically, the time horizon value can be any value as long as $2 * maxSpeed * \tau < visionrange$, where $2 * maxSpeed * \tau$ is the distance between two agents that can be covered in τ seconds. (i.e. they both move their maximum speed directly towards each other.)

- V_s is the steering velocity to drive the agent approaching the lane behind the target agent. It decreases as the distance between the two agents decreases.
- V_r is the steering velocity to reduce the agent's speed so as to match with the target agent. It decreases as the distance between the two agents decreases.
- d_f is the distance behind the following target. It is a distance to maintain during the *following* process. Its value depends on the personal space and individual preferences
- d_s is the slight deviation of the following position behind the targeting agent. Its value can be random within a range.

Figure 5.9: Execution of the *follow* steering strategy.

From the modeling point of view, the execution of ‘follow’ steering strategy can be modeled through two consecutive processes, *target selection* and *target approaching*. Once an agent selects the ‘follow’ steering strategy through the decision-making process, it needs to identify a potential target to follow. This target could be an individual agent or a group of agents in front, moving in the same general direction as the observing agent. The target is selected based on the empirical instructions of the ‘follow’ steering strategy corresponding to the prototypical pattern that has been matched in the decision-making process. In this model, the relative position and the perceived size of the group affect the target selection. In general, people tend to follow bigger groups and prefer to minimize deviation from their current moving direction. In the representation of the prototypical STP for the ‘follow’ steering strategy, such observations are reflected from the consecutive number of sections with value “1” that are located nearer to the central column(s) of the slices in the first row of the concrete STP. In the case of multiple sections with value “1”, the agent will randomly choose one of the agents as the target to follow.

After the target is selected, an agent will start to approach the virtual lane behind the target. The execution process of the ‘follow’ steering strategy is illustrated in Figure 5.9. Some pedestrian studies reveal certain behavioral habits of pedestrians

in their following behaviors. As discussed in [230], pedestrians prefer to follow others slightly to the left or right hand side behind the target instead of following on exactly the same line. By doing so, the pedestrian behind will not be blocked by people in front so that he/she can still monitor the situation in front. Applying such findings in the model, the deviation distance parameter d_s is used to model the minor deviation of the following position behind the target. The preferred gap distance d_f between the pedestrian and the target to follow is determined by the personal space and individual preferences as well. During the lane approaching process, the pedestrian behind slows down gradually in order to match the velocity with that of its target. In fact, empirical studies [63, 140, 225] have shown the fundamental diagrams of the relationship between the speed and the density. In recent studies by Seyfried's group [185], they conducted controlled experiments for movement in single file (unidirectional), used the distance with the people in front to estimate the density, and pointed out that an almost linear relationship can be established between the distance ahead with other agents (i.e., the target to follow in our case) and the speed of the agent in the medium to dense scenario (where the speed of the subject tested is generally under 1.0 m/s). Such findings have been applied in the model by reducing the magnitude of the steering velocity to approach lane V_s and the steering velocity to reduce speed V_r as the agent moves closer to the target. Particularly, we define three different phases (similar to the term "domain" used in Sefried et al's work) to define the quantitative relation between the speed of the agent and the distance between the agent ahead (i.e., the target to follow). In the first phase, where the distance is still larger than a distance of $1.5 d_f$, we use an exponential function to model the speed reduction of the agent based on our observation that pedestrians seem to reduce speed faster initially in the 'following' process. When entering the distance of $1.5 d_f$, the speed of the agent reduces linearly to match with the target in the second phase (as inspired by Seyfried et al's work). In the last phase when the distance between the two agents is very close (i.e., smaller than d_f), we let the speed of the agent drop exponentially fast such that it can quickly match with the target's speed. The execution process finishes when the agent arrives at the target position behind the target, and the difference in velocities between the agent and the target is within a certain threshold value.

5.4.3 Overtake

Besides 'following', 'overtaking' someone in the front is another commonly observed steering behavior of pedestrians. The notion of 'overtake' we take as an appropriate steering strategy refers to:

An active cognitive process where an individual decides to catch up and then move ahead of people in front of them in order to achieve certain goals (e.g., to maintain higher speed while avoiding collisions with people who are moving slower in front).

The adoption of the *overtake* steering strategy may be because of either internal drive of the person or the external situation. Internal drive of the person may be due to many factors, such as the faster physical speed of the person, the motivation of trying to reach the destination earlier, etc. In order for an agent to select the overtake steering strategy, it must *intend* to overtake due to its internal drive. In terms of the configuration of the external situation, there are two types of constraints. On the one hand, the vicinity in front of the individual is blocked by someone or some group moving slower. Thus, it is necessary for the individual to overtake them to fulfill the internal intention. On the other hand, although it is necessary to overtake others in front, the individual probably will not overtake until she perceives feasible spatio-temporal constraints that allow her to do so. Such behaviors also reflect the social norm [230] to prevent collisions with others.

From the modeling point of view, the execution of the ‘overtake’ steering strategy can be modeled through three consecutive (cognitive and behavioral) processes, *target identification*, *catch-up* and *pass*. Similar to the ‘follow’ steering strategy, an overtaking target needs to be identified as the first process of execution. The selection of the overtaking target is also based on the matched concrete STP in the decision making process. Overtaking behaviors usually occur when a pedestrian moves faster than someone in the front. If the pedestrian intends to move faster, she has to overtake the people while avoiding collisions with the slow mover in the front. As reviewed in [30], pedestrians who intend to move faster will constantly look for empty space for overtaking in front of them. We have also observed that *pedestrians usually overtake the slower individual or groups in the front that are less deviated from their current moving direction*. Thus, to identify the target to overtake, we look for either “01” in the left half or “10” in the right half of the first slice that is less deviated from the central columns in the concrete STP. An agent that occupies the section with value “1” is chosen at random as the target to overtake.

Once the target to overtake is identified, the ‘overtake’ steering strategy can be executed through the *catch-up* and *pass* phases. Previous work, (e.g., [174]), also adopts a similar approach to divide and model the overtaking process through different phases. The overall execution process is demonstrated in Figure 5.10.

 Figure 5.10: Execution of the *overtake* steering strategy.

In the first phase, the agent will not only deviate from its current moving direction towards the space beside the target (see steering velocity to deviate away from the target V_d), but also increase its speed (see steering velocity to increase the speed V_i) within a comfortable range (i.e., smaller than the maximum speed). The agent will constantly compare its velocity with that of its target while monitoring the target's relative position at the same time. This phase is complete when the agent reaches the space beside or slightly behind the target with a reserved distance d_d . In the second phase, the agent gradually adjusts its velocity towards the current goal (see V_g) as specified by the path-planning layer in order to pass ahead of the target and stop deviating further away from the target. The agent in this phase does not adjust its velocity with the target as the reference, but is directed by the current goal. The speed of the agent also gradually reduces (see V_r) to resume its preferred speed prior to the overtaking process. This phase to pass the target and thus the overall overtaking process finishes after a limited number of frames (see T_x), which is set as $0.1 * T_{catch}$ currently.

5.4.4 Side-Avoid

The “follow” and “overtake” steering strategies are adopted by pedestrians to avoid collisions with people that are moving in the same general direction as them. Besides these steering strategies, another steering strategy is often observed when pedestrians try to resolve potential collisions with pedestrians moving towards them. The notion of “side-avoid” we define as a steering strategy:

An active cognitive process, where an individual perceives an individual or group of people coming towards her that may result in potential collision and tries to proactively avoid them.

In the case where an individual passively adopts instinctive reactions to resolve an imminent collision, we do not consider such reactive behavior as a steering strategy. Most existing models use the concept of *collision-avoidance* referring to the maneuvers in the locomotive level, which is different from the strategic steering behaviors defined here. With the side-avoid steering strategy, an agent resolves collisions with other agents moving towards it. However, collision-avoidance in the action level is not *only* achieved through side-avoid steering strategy but also the other two steering strategies as discussed above.

From the modeling point of view, the execution of the *side-avoid* steering strategy is similar to the ‘overtake’ steering strategy. We have defined the execution of the ‘side-avoid’ steering strategy through *target select* and *deviate*.

The selection of the target to side-avoid is based on the empirical instruction corresponding to the prototypical pattern that triggers the selection of ‘side-avoid’ steering strategy. In the situation where this steering strategy usually occurs, there are either individual or group of pedestrians coming towards the observing pedestrian and the potential collision may occur if no action is taken by both parties. In the model, the target to side-avoid in such cases is selected as an approaching agent with sufficient space beside it. In some pedestrian studies [54, 230], the space required for the side-avoiding process is minimal as they believe that both avoiding parties generally behave in a cooperative manner, since they are likely to see each other in such a situation, and are able to create space through sliding or rotating their body. However, we use the space beside the potential target to execute the side-avoid steering strategy (see Appendix A). This is because the side-avoid steering strategy involves proactive planning to minimize the chance of needing to avoid an imminent collision. In such situations, if the pedestrian could not perceive the space, he/she

would not be able to plan such a steering strategy, instead, instinctive reactions are probably adopted. Accordingly, we can distinguish the reactive ‘avoiding’ maneuvers (instinctive reaction as generated by the RVO2 motion control) and the side-avoid steering strategy. Thus, to identify the target to side-avoid, we look for either ‘0 – 1’ in the left half or ‘–10’ in the right half of the first slice starting from the central columns in the concrete STP. An agent that occupies the section with value ‘-1’ is chosen as the target.

Figure 5.11: Execution of the *side-avoid* steering strategy.

Once the side-avoid target is identified, a sequence of preferred velocities are generated to execute the ‘side-avoid’ steering strategy as shown in Figure 5.11. The execution process is modeled as a *deviate* phase. The observing agent deviates away from its original moving direction to avoid the target by a deviated distance (see d_d). A symmetry breaking process takes place here, where agents try to guess how the other will avoid themselves. This reflects the cooperative nature of pedestrians in their interactions when they can see each other [230]. The deviation phase terminates

once there is enough space between the observing agent and the target for them to move towards their current goals. To check whether the deviation so far is enough to avoid collisions with each other, the agent tests collisions through the locomotive motion control mechanism (e.g., RVO2) at each simulation frame using the testing velocity $\vec{V}_g$ towards the current goal. The magnitude of this testing velocity is set with the current speed of the agent. The overall side-avoid steering strategy completes if the testing velocity does not cause a collision with the target.

5.5 Summary

In this chapter, we have described an agent-based Pattern-Based Steering model (PBS) for pedestrian simulation. PBS utilizes the spatio-temporal patterns (STPs) and the corresponding steering strategies to mimic the experiences of pedestrians in their strategic steering choices. The model follows the perceive-decide-act paradigm and aims to model the local path determination layer in the tri-layered navigational behavior modeling structure. The potential advantages of this pattern-based approach include:

- *Human-like perception*: human are efficient in perceiving the environment. They are capable of handling multiple chunks of information at the same time in a parallel manner. In our approach, spatio-temporal information is implicitly processed in a parallel manner and the visual perception of an agent is formed in an aggregated form of a concrete STP.
- *Naturalistic decision making*: the decision on steering strategies are based on the results of the matching between the perceived concrete STP and the prototypical STPs. Experience instances are naturally implemented as the prototypical STPs and their corresponding steering strategies.
- *Realistic strategic level steering behavior*: the steering behaviors are modeled through an additional layer at the strategic level above locomotion. Such an approach naturally categorize the basic actions of pedestrians in terms of steering strategies, and provides a more intuitive understanding of pedestrians' steering behaviors.
- *Intuitive for modelers to use*: the pattern-based decision-making architecture allows modelers to understand and model the strategic steering behaviors of individual agents intuitively corresponding to the perceived patterns.

- *Extendibility*: the pre-defined prototypical patterns naturally represent the experience instances of a pedestrian in coping with specific situations in a particular scenario. The proposed *Pattern Description Method* (PDM) allows model developers to easily and intuitively develop different patterns to mimic different experiences of the agents to cater for specific applications.

Chapter 6

Model Evaluation

One of the most challenging aspects in pedestrian simulation research is evaluation. The autonomous behavior of individuals and their complex interactions result in dynamic crowd behaviors in real life. This makes it difficult to evaluate, even to compare simulation results with reality. However, despite the challenges, it is necessary to evaluate a computational model before using it in real world applications. Evaluation can be conducted with focus on different aspects of the model, of which model validation is an important yet challenging task for pedestrian simulation models. In this chapter, we address the validation methods for the PBS model. Different types of model validation and techniques that have been previously applied for pedestrian simulation will be first reviewed and discussed. Reviewing previous work provides two implications on the validation work of the PBS model. First, it helps us identify the types of validation which previous works fail to satisfy and analyze the feasibility in achieving such levels of validity. Secondly, it provides standard methods and some commonly used metrics that can be used in validating the PBS model. Based on these implications, validation methods for the PBS model through three stages will be outlined at the end of this chapter.

6.1 Introduction

6.1.1 Different Aspects of Model Evaluation

Pedestrian behavioral simulation has been an active research topic in recent years, many simulation models have been proposed that try to mimic pedestrians in real life and produce similar behavior through simulation. Although these simulation models have addressed different research issues, little attention has been accorded to evaluating the models and their results systematically.

model evaluation, according to [214], is defined as the systematic acquisition and assessment of information to provide useful feedback about an object. Applying the definition in our context, the “object” refers to the pedestrian simulation model being evaluated. Both good and bad aspects of the model should be reflected through the evaluation process. In the context of computational models, a comprehensive model evaluation could be conducted through several sub-dimensions focusing on different aspects of the model, which may include, but is not limited to: verification, validation, scalability, flexibility and extendibility, computational efficiency and usability.

Along these dimensions, *model validation* is one of the most often used and abused terms in computer modeling for behavioral simulation as suggested by Still [201]. However, it is probably the most relevant and important aspect in model evaluation for agent-based models that aim to achieve realistic and natural crowd behavior simulation. We shall use the term validation defined as “substantiation that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model” [180]. In this thesis, we focus on the validation of the PBS model while being mindful that other dimensions of evaluations are also important.

6.1.2 Types of Validation

Validation is essential for simulation; without some form of validation, there can only be limited confidence in the accuracy of the model. One central motivation for ABM is that the behavior of the system emerges dynamically at runtime. This unpredictable nature of the system makes tracing cause and effect relationships very challenging. The complexity and arrangement of the vast numbers of agents will also typically lead to overly parameterized models, which in turn can lead to the problem of impossible falsification [105]. These issues make agent-based models very challenging to validate and current approaches and techniques are still under-developed with many philosophical and methodical questions remaining unanswered [133]. These challenges in ABM regarding validation become even more significant when trying to model natural systems like crowds, which involve human behavioral aspects. For these types of model, challenges occur in many aspects of validation: collection of appropriate data at different levels (i.e. aggregated level and individual level etc.), the non-determinism of human free will, the greater emphasis on transient dynamics (i.e. the steering behaviors themselves rather than the consequence of collision avoidance through such behaviors) and the difficulties in capturing output in a reasonable way

(i.e. how to measure whether the behaviors of agents from a model is natural or realistic), etc. Establishing hard validation for such systems is very difficult [105, 133]. Some even argued that validation is a misnomer [209] in the sense that no model is valid to suit every data set and case, but it can only be validated in a certain context. It is thus perhaps better to state that one gains confidence in the simulation model through proper validation methods for a particular application domain [229, 235].

There are various approaches to achieve different types of validity for a computational model. Naylor and Finger [141] formulated a three-step approach to model validation that has been widely followed. In this approach, *facial validity* is first tested; then one needs to validate model assumptions (*assumption validity*); the model input-output transformations are finally compared to corresponding input-output transformations for the real system (*functional validity*). Others tried to achieve the three levels of validity proposed by Zeigler [241] as the *replicative*, *predictive* and *structural* validity denoting that the model is able to reproduce the given or historical data, the unknown or future data and the original structural relationship. Each level is considered to be more challenging to achieve than the previous one.

Trochim and Donnelly [213] proposed to classify validation and the levels of validity in two different dimensions. In one dimension, four validation levels are discussed. *Conclusion validity* refers to the relationship of model variables corresponding to the observations in the real system. If the relationship is causal, *internal validity* is achieved. *Construct validity* requires that the causal relationship reflects the modelers intention of constructing the model. *External validity* is a higher level validity, which can seldom be satisfied. In the other dimension according to measurement methods in validation, they defined *concurrent validity*, *convergent* and *divergent validity* of a model. The first one investigates whether the model is able to generate different results on different parameters in the intended way; the later two focuses on the model results compared with other models representing the same system.

Recently, Klügl [105] proposed to characterize validity along two dimensions. One is based on the nature of the test methods and the other is based on the addressed elements of the model. Along the first dimension, *facial validity* and *empirical validity* can be achieved through natural human intelligence of Subject Matter Experts (SMEs) and quantitative measures and tests respectively. While in the second dimension, *behavioral validity* and *structural validity* can be evaluated through the input-output transformation and the internal causal relationship respectively. Under this categorization, *facial validity* of a model is established when the model appears reasonable

to the model users and other SMEs for its specific application [14]. *Empirical validity* of a model refers to the statistical evidence that a diagnostic instrument measures what it is supposed to measure [151]. In the context of ABM, it is derived from empirical validation uses statistical measures and tests to compare key figures produced by the model with numbers gathered from the reference system. The *behavioral validity* may also be referred as functional validity, which assesses the model through the input-output behavior or results of a model, whereas the *structural validity* refers to the validity of the internal structure such as the causal relations between variables or the reasoning of agents in a model [105].

Klügl's categorization of types of validation is relatively comprehensive and well organized in the context of ABM for human behaviors such as pedestrian simulation. Although different terms have been proposed in other approaches, most of them are similar and can be equated to the corresponding validation in Klügl's categorization. For example, the *assumption validity* proposed in [141] can be considered as part of the *structural* validity in Klügl's categorization. The *replicative* and *predictive* validity as proposed by Zeigler [241] focus on the validation of a model through its results on the contrary to the model structure. The *conclusion* and *construct* validity as proposed by Trochim and Donnelly [213] can be considered as correspondents of the *behavioral* and *structural* validity as proposed by Klügl. The *concurrent*, *convergent* and *divergent* validation categorization is based on the measurement methods such as model alignment, which is slightly different from Klügl's categorization. Nevertheless, it can be considered as a sub-dimension of the *behavioral* validation as discussed in [105]. We adopt Klügl's categorization of model validation in the following section when reviewing previous work on pedestrians simulation model validation.

6.2 Validation Techniques and Previous work

Many validation techniques have been proposed to validate models in different applications. Balci [10, 11] illustrated more than 40 techniques in model validation and verification. Xiang et al [234] discussed several such techniques in the context of ABM. For instance, to represent output from *animation* or *graphical representation* and apply *simulation tracing* or *Turing test* on SMEs to judge the facial validity of the model; to apply *statistical test* on empirical data; to identifying critical parameters through model parameter *variability tests* and *sensitivity analysis*. In addition, they mentioned model-to-model comparison or *model alignment* [7], which was also considered as a validation method in [105]. In pedestrian simulation model validation,

some of these validation techniques have been applied, but in a rather ad-hoc manner as pointed out by [12, 13]. In this thesis, the author tries to summarize some of these work according to the two dimensions of validation types proposed by Klügl [105].

6.2.1 Facial Validity vs Empirical Validity

Along the first dimension of validation types, validation can be conducted subjectively by SMEs or assessed objectively through quantitative measurements and statistical tests. A large amount of previous work [106, 126, 139], in general, deduced *facial validity* of their models through demonstrating animation as the simulation results for different test cases from simple interactions between two agents to more complex emerging crowd level behaviors. The SMEs trace these results to identify possible drawbacks of the model. Such tracing methods are still largely involved and the author agrees on its role in the overall validation process to provide feedback to the model development because of its relatively straight-forward judgments (compared with the statistical tests). Other than animation and tracing, immersive participation is another technique in face validation. Pelechano and the Gamma group at University of North Carolina [160] proposed to use the concept of *presence* to validate the crowds through an immersive approach by involving participants in a crowd in Virtual Reality. Egocentric features such as shaking, continuous movement, overlapping, communication and pushing were used to evaluate the conceptual *presence*. They also compare different crowd models such as social forces, rule based, cellular automata and HiDAC based on such features in their validation work.

Facial validity may not be sufficient to provide accurate assessment of the model for some applications. In such cases, quantitative validation approaches are also applied. The early validation work involved quantitative measurements focusing on the macroscopic pedestrian dynamics such as the density, average speed and flow rate of the crowd. In particular, the fundamental diagrams [49, 210] of pedestrian movements between density and speed; density and flow are widely used to validate the overall emerging crowd behaviors of a model [185, 201]. Helbing and Johansson [70, 71, 91, 92] analyzed the self-organizing behaviors of crowds through experimental studies, they calibrated and validated a social-force model according to the findings from experiments and video data. Berrou et al [17] validated their model by comparing real and simulated flows and densities at bottlenecks. In particular, they discussed methods used to extract microscopic and macroscopic data from video recordings of real-life pedestrian crowds. The extracted data was used to form demographic profiles

of pedestrian attributes as the inputs of the model. The collective observable and behavioral patterns from the experiments were used to benchmark simulation results. A similar study on flow at bottlenecks was done by Kretz et al [110]. Davies et al [38] focused on the analysis of crowd movement and densities in built-up environments using image processing. They pointed out that it is a challenge to automatically acquire crowd data and features when the density is high and summarized several existing image processing techniques for this purpose. Lerner et al [121] adopted a data driven evaluation approach on crowd behaviors and pointed out the use of state-action pairs in the example-based approach. A state is defined as the densities of the people in different regions surrounding the subject person. An action is defined as the subject person's positions along a two second long trajectory interval. Based on video footage of real crowds, a database for such state-action examples is generated. They also proposed to use similarity measure (density measure) to interpret the level of "naturalness" of the behaviors. Banerjee et al [12] suggested a system for quantitative validating agent based crowd simulation systems. They used a novel, automated method for comparing the results (the movements) produced by the simulation against videos of crowds evacuating from a stadium that are available from CCTV. The area in the simulation is first divided into regions. The number of agents passed through each of these regions along time series is compared against the data collected from the video.

In the work listed above, crowd features at the macroscopic level were studied extensively and several metrics such as density, average speed and flow rate have been measured for quantitative model validation. On the contrary, microscopic level data of pedestrians is difficult to collect and analyze from videos of uncontrolled crowd scenarios. The study of microscopic pedestrian behavior has instead relied more on controlled experiments so far. Daamen and Hoogendoorn [34, 35, 75, 76] performed a set of experiments to observe pedestrians in uni-directional and bi-directional traffic, crossing traffic and at bottlenecks. They identified several microscopic movement features of the participants such as step frequencies, latitudinal and longitudinal space usage by the participants during interactions in addition to the macroscopic phenomena such as lane formation, and sliding waves front in crossing flows. Brogan and Johnson [23] compared real walking paths from their experiments with simulated paths quantitatively using three different metrics: the distance error, that is the mean distance between the real and the simulated path for all simulation time steps, the area error, that is the area between the two paths, and the speed error,

that is the mean difference in speed between the two paths for all simulation time steps. Paris et al [155] used a predictive extrapolation method to solve interactions between pedestrians and avoid inter-collisions. They conducted indoor experiments on simple interaction scenarios to capture the motion data such as speed and direction along time during interaction and used such data to calibrate and validate their model. Similar experiments on simplified cross interaction scenario were done by Pettré et al [162]. They proposed an experiment-based modeling, simulation and validation of interactions between virtual walkers. This started with experiments to collect data such as time to reaction and its corresponding reaction distance for participants in pair-interactions, this was then extended to multiple interaction cases. They compared the simulated trajectories with the real ones in a similar way to that described in [23]. Recently, an approach similar to PBS, which introduces the concept of simple cognitive heuristics has been proposed by Moussaïd et al [135, 136]. They have conducted a series of laboratory experiments over several years to determine the behavioral mechanisms underlying different behavioral patterns and provided solid evidence for their models on the quantitative agreement with a large variety of empirical and experimental data. This work presents good examples for research on the validation of pedestrian simulation models through using microscopic level experimental data.

6.2.2 Behavioral Validity vs Structural Validity

Along another dimension of validation type, models are assessed either on their capability of producing similar results on a given set of input or representing the internal structure of the real system. In validating results or the input-output transformation of a model, in addition to the detailed examination of behaviors for individual agents at the microscopic level, functional validity of the model can be demonstrated through replicating different emerging behaviors that are commonly observed in real pedestrian movement or generated by other similar models at different aggregated levels, such as lane formation, finger-crossing effect, edge effect, wake effect etc [59, 148, 160]. In particular at the steering behavioral level, Singh et al [196] proposed a benchmark suite for evaluating steering behaviors of a model. More than 20 scenarios categorized into different groups were proposed; three metrics, the number of collisions, time efficiency and the effort efficiency together with a weighted scoring method are used to compare different steering algorithms quantitatively. In summary, most validation works have been conducted through assessing the results of the model.

On the contrary, the structural validation of a pedestrian simulation model is challenging and seldom considered. Current work on structural validation of pedestrian simulation models mainly relies on their facial validity in trying to represent some aspects of human factor realistically. Most of these models are constructed based on certain assumptions or theories that are believed to represent human characteristics naturally from other research fields such as psychology and social science. Other than the supportive arguments taken from the existing literature, it is difficult to validate model structure quantitatively due to lack of consensus on quantifying different factors on the real pedestrian behaviors. In this study, the PBS model has been developed based on the assumptions as described in Chapter 3, which presumes that pedestrians can synthesize the visually perceived information comprehensively in an efficient manner, and there is correlation between the experience of a pedestrian and their steering choices. Based on these assumptions, we have proposed the pattern-based approach to mimic the cognitive process involved during pedestrians' steering behavior. Although evidence taken from the literature has added confidence to the structural validity of this model, it is still an open research question on how people perceive the spatio-temporal information and how they make use of such information for decisions. Researches are currently trying to study the Brain-Computer Interface (BCI) and to interpret the brain waves through electroencephalography (EEG), magnetoencephalography (MEG) and functional Magnetic Resonances Imaging (fMRI) technologies and restore the synthesized vision from these signals [131]. However, to the author's knowledge, such technology can, as of now, only restore simple images with limited accuracy and is not mature enough to be applied to studying the pedestrians' minds in their steering process, where much more complex spatio-temporal information is involved. To this end, one should realize that the validation of pedestrian simulation models on the structural level is a very challenging research issue. It may be appropriate to aim for other levels of validity first through facial validity and functional validity, then to provide evidence to show that a model is capable of representing the original pedestrians in certain aspects for a specific application domain.

Simulation results of a model can either be assessed subjectively (facial validity) or quantitatively (empirical validity). Due to the lack of sufficient amount of microscopic behavioral data on pedestrian movement, controlled experiments on simple scenarios would help investigate a model in much detail under such scenarios. In addition, comparing the results of a model with other well established models (model alignment)

is also an important and widely adopted method to assess results. The comparisons can be based on different qualitative and quantitative metrics to demonstrate the behavioral validity of the model with particular applications. The results of the a particular model can also be explained through the structural construction of the model, which may indirectly provide structural validity to the model. Last but not least, the simulated pedestrian behaviors emerge from complex interactions among individuals in an agent-based model, sensitivity analysis helps to further test the robustness and performance of the model. Based on these observations from the existing work, we propose to validate the PBS model through a three-stage validation method.

6.3 Validation Method for PBS model

In order to validate the PBS model, we propose a three stage validation approach. First, we used a set of basic scenarios to test the simple steering strategies proposed in the model and to validate the model thoroughly through comparing the results qualitatively and quantitatively with both experimental data and simulation results of other models. At the second stage, we adopt simulation scenarios from existing work that involve more complex crowd interactions to test the PBS model against other models. At the last stage, we conduct sensitivity analysis on the PBS model to demonstrate its robustness and to identify the strength and limitation of the model. The methodology is further elaborated in the subsections as follows while the results will be discussed in the next chapter.

6.3.1 Stage One: Experimental Studies (Simple Scenarios)

At the first stage, we selected several basic scenarios to test the PBS model with comparison to the real data collected from controlled experiments and the results of other simulation models. Three controlled scenarios have been chosen for conducting experiments and simulations. There are mainly three reasons to choose such scenarios. First, to evaluate the several simple steering strategies we propose in the corresponding scenarios as the basis of more complex emerging behaviors. Second, to quantitatively measure the “similarity” of the simulation results with the actual movements using the data collected through the field experiments. Controlled experiments are still the preferred methods of collecting specific microscopic level data on pedestrian movements over the video-streams analysis on large scale crowd videos due to the higher

precision and feasibility of intention capture of the participants [34, 35, 155]. To facilitate the data collection and analysis process, we used a simple protocol to control the experiments in these scenarios as will be detailed in the next chapter. Third, to highlight some of the model issues, we analyze details of the simulation results statistically with comparisons to the experimental data and simulation results of other models.

To achieve the validation in this stage, we first designed the three scenarios and devised the experiment. After collecting data from the experiments, we setup the same scenarios and produce the steering behaviors of the agents through simulation in both the PBS model and another benchmark model we chose to compare with. Data analysis was then conducted to indicate the strengths and weaknesses of the PBS model over the benchmark model with the experimental data. At the end of this stage, conclusions can be drawn on the facial and partial functional validity of the PBS model, being capable of replicating the interactions of pedestrians in such scenarios more closely than the other model(s).

6.3.2 Stage Two: Model Alignment (Complex Scenarios)

In the second stage of validation, we demonstrated how the PBS model can produce some more aggregated level of behaviors through scheduling and execution of the simple steering strategies. Many different models of crowd simulation have been proposed, but no model can produce all possible crowd behaviors [89, 244]. Nevertheless, a model needs to be tested in more complex scenarios for its application in generating group or crowd level behaviors for wider applications in pedestrian simulation. *Model alignment* is a common way to validate a particular model against other similar models through comparing the input-output relationship. Many previous validation work [97, 148, 162] of pedestrian simulation model adopted such an approach. Based on the comparison of the results with other existing models, the performance of the model can be both subjectively judged by an Subject Matter Experts (SME) or quantitatively assessed through some metrics that reflect the motion characteristics of pedestrians in such scenario.

To assess the simulation results of a model in a more complex scenario is more challenging than the basic scenarios. First, it is much more difficult to conduct experiments and collect data effectively and accurately from such scenarios, where close proximity among individual participants and interactions frequently occur. Besides, individual behaviors may be difficult to analyze due to the complex interactions among

them. Instead, some commonly observed crowd phenomena such as lane formation and the edge effect have been proposed and widely agreed as common phenomena observed in human crowds [59, 61, 136, 148]. These phenomena reflect natural crowd dynamics exhibited in real life. At this stage, we adopt several commonly used testing scenarios from previous work, where more agents and complex interactions are involved in the simulation. We tried to analyze the PBS model through its simulation results with comparison to the benchmark model(s). Through these tests, we functionally validated the PBS model.

6.3.3 Stage Three: Sensitivity Analysis

Through stage one and two, it is demonstrated that heterogeneous behaviors of agents even in the same situation can be generated in the PBS model. Such heterogeneity may be attributed to design or as an unexpected side effect of the random variables of the model. On one hand, such heterogeneity is achieved through the design of the model to deliberately imitate the behavioral variations in pedestrians movements. As illustrated, different steering strategies may be chosen by an agent subject to the match between the perceived spatio-temporal patterns and its prototypical patterns. Personal traits such as the *commitment level* and the *preferred speed* of the agent affects the matching results, thus generating different steering behaviors. On the other, simulation results may vary significantly at different parameter values due to the complex interactions among individual agents. Therefore, sensitivity analysis is conducted to identify the significance of different key parameters. At this stage, we replicate the simulation using different values of a selected set of parameters of the PBS model (i.e. personal space factor of agents, commitment level of agents and the variance in preferred speed of agents). We then analyze how simulation results vary according to the metrics used in the second validation stage, and to examine the impacts of different parameters to the emerging behaviors of agents.

6.4 Summary

Model evaluation, in particular, validation is a challenging research issue. Through the discussion in this chapter, we have reviewed several validation types and validation techniques in each validation type that have been applied in pedestrian and crowd simulation models in the previous work. In general, the functional validation on the simulation results remains the focus of the feasible validation work because structural

validity of a model is hard to achieve due to the lack of knowledge and consensus of real pedestrian systems in the real world.

Based on the review of existing work on validation of pedestrian simulation models and the approaches that have been commonly taken, I proposed a three-stage validation approach to validate the PBS model. In the first stage, a comprehensive investigation of the interactions of pedestrians in some basic scenarios was first studied through experiments and comparison of simulation results of different models with the experimental data. In the second stage, the PBS model was validated through model alignment with existing models on more complex scenarios. Some crowd features are used as the metrics to compare and assess the simulation results. In the last stage, sensitivity analysis of the model parameters was carried out to identify the key parameters and the strengths and weaknesses of the model. Following this method, we have conducted a series of experiments including both field experiments and simulation. The results and analysis will be elaborated and discussed in the next chapter.

Chapter 7

Results and Discussion

In this chapter, we describe the experiments including both the field experiments and the simulation studies that have been conducted. We analyze the results of the PBS model and evaluate the model according to the three-stage validation method proposed in the previous chapter. In the first stage, the validation consists of experimental studies of pedestrians' steering behaviors in three simple scenarios. Simulation results of the PBS model and other existing well known models are compared with the experimental data, both qualitatively and quantitatively. In the second stage, more complex interaction scenarios, commonly adopted in the crowd simulation literature, are used to test the PBS model. We analyze and categorize the scenarios and show the corresponding performance of the PBS model. Model alignment is utilized in this stage to validate the PBS model through comparisons with other models. In the last stage, a sensitivity analysis is conducted on several assumed key parameters of the PBS model to quantify the importance of the assumed key parameters and to demonstrate the robustness of the PBS model for the purpose of modeling realistic pedestrian steering behaviors.

Due to the length of chapter, we quickly summarize the validation process and the objectives of each validation stage in Table 7.1. Details on the experimental study and simulation results are discussed in this chapter and Appendix B. The key findings from each of the validation stages will be summarized in Section 7.4.

7.1 Validation through Experimental Studies

7.1.1 Experimental Studies

We first conduct several controlled field experiments to study the interaction among individual walkers and their steering choices. The experimental data is then used in

Table 7.1: Overview of the validation process.

Validation Stage	Methods	Objectives
One (Section 7.1)	Field experiments (selected scenarios)	<ul style="list-style-type: none"> • To study various motion features of participants during their interaction.
	Simulation studies (selected scenarios)	<ul style="list-style-type: none"> • To validate the PBS model thoroughly through comparing results qualitatively and quantitatively with both experimental data and two other models
Two (Section 7.2)	Simulation studies (Standard test cases under more complex scenarios)	<ul style="list-style-type: none"> • To show that the PBS model can be used to simulate collective pedestrian dynamics under different complex scenarios. • To demonstrate that the PBS model can perform comparatively well in various complex scenarios, and thus to demonstrate the robustness of the pattern-based approach.
Three (Section 7.3)	Sensitivity Analysis	<ul style="list-style-type: none"> • To demonstrate the robustness of the PBS model • To study the impact of key model parameters.

two ways. First, some of the data such as the average moving speed is used for simulation initialization. Secondly, relevant metrics are extracted from the recorded data and used as benchmarks to compare with the simulation results of existing models.

7.1.1.1 Scenario Design

In our experiments, three movement and interaction scenarios are designed to capture real interactions among three participants as shown in Figure 7.1. In all three scenarios, an area 13.5 m in length and 2.5 m in width is considered as the constrained space, where interactions of participants occur. Different destination are marked on the floor as shown in Figure 7.1 for different scenarios. The scenarios are designed to capture different steering strategies developed by the participants in perceiving particular spatial constraints in the scenario, and to quantify the trajectories made in terms of velocity and orientation changes along time. Such a space can be taken as a representation of many places in real life situations, where bi-directional movement is often observed. Each scenario involves three participants. In the theoretical basis discussed in Chapter 3, we assume that pedestrians are capable of steering without much dedicated effort. In order to shift attention of the participants from their movement, we assign some light cognitive tasks such as simple algebraic calculation to each

(a) scenario one

(b) scenario two

(c) scenario three

Figure 7.1: Three scenarios used in the experimental studies.

of the participants.

In *Scenario One* (Figure 7.1(a)), participant 2 walks from left to right in the field, while another two (1 and 3) walk from right to left. Their initial positions are set as shown in Figure 7.1(a). They are initially 10 m away from each other along the (longitude) moving direction. Vertical to their predominant moving directions (i.e., left to right or right to left), they are initialized with positions such that they *have to* adapt their trajectories in the moving process in order to avoid collisions with each

other. The two participants walking from right to left are set with an initial separation of 1 m. Such a setting is chosen to preserve certain personal space preferences of pedestrians, as observed in real life situations, while keeping them close enough for them to be perceived as a group by the other participant. The participants are told to walk at a comfortable speed. Their goals are to cross a pre-marked area on the other side of the passage as indicated in yellow color in Figure 7.1(a). This scenario is intended to observe and record the *side-avoid* steering strategy of the participants.

In *Scenario Two*, all three participants are told to walk from their initial positions towards the same destination area on the left end of the passage. Two (1 and 3) are initialized at a distance of 6 m away from the destination and they are told to walk slowly together towards the destination. The other (2) starts from a distance of 5.5 m behind 1 and 3, and is told to walk fast towards the destination as shown in Figure 7.1(b). In the context of this study, by “walking fast”, we intend to have the participant behind reach the destination before the two in front. However, such fuzzy concepts are difficult to control in the actual experiment. Theoretically, we should not try to influence the preferred walking speed of participants, so as to preserve the natural movement as much as possible. However, we need to control the experiments to create the desired interactions for this scenario. In order to achieve this, we conduct an initial training session so that the participants understand the fuzzy concept “fast” or “slow”. According to the average recorded walking speed of the participants, we roughly categorize them into the *fast* and the *slow* groups. Nevertheless, we do not explicitly instruct the fast participant to reach the destination first during the experiment. Thus, the one behind may not always reach the destination before the other two. Only if she has done so, the video for that session is used for further analysis. This scenario is used to observe and record data of the interaction involved in the *overtake* steering strategy.

In *Scenario Three*, the setup is similar to that of Scenario Two. However, a narrow virtual tunnel of 1.8 m in width is imposed on the way towards the destination as shown in Figure 7.1(c). As observed in the initial testing sessions, such a width allows only three participants to walk side-by-side with little space left in the latitude dimension. Two participants (1 and 3) are initially positioned 6 m away from the destination and 1 m away from the tunnel. They are told to walk slowly towards the destination. The other participant (2) starts from 4 m away behind the previous two and is told to walk fast towards the destination. Congestion is imposed by the narrow tunnel and the slower walkers in front. The participants are not allowed to communicate with

each other. This measure is done to ensure that their behavior and interaction will not be influenced in any way by any external factor like communication. (e.g., [161] observed different shapes of a group in different communication-existing scenarios). In each experiment session, we select a participant from the “fast” group to participate in the session. This scenario is used to observe and record data of the *follow* steering strategy.

7.1.1.2 Physical Setup and Experiments

The experiments are conducted at an outdoor passage under a building at the Nanyang Technological University, Singapore. A video camera with a resolution of 1280×720 was fixed with a horizontal tripod at a height of 11.8 m above the ground, where the actual experiments are conducted as shown in Figure 7.2. The camera is calibrated with the markers we make on the floor. The height is selected as a trade-off between the resolution of the participants in the video and the range covered on the ground. A wide-angle lens (Tokina 11-16 mm f/2.8 AT-X) with good distortion control is used to capture the whole area. We select an area of $13.5m \times 2.5m$ in the center of the view to be the area of interest for experiments. At this area, the distortion of the lens is minimal and thus can be neglected. The experiment field is marked with marker lines on the floor for two purposes. One is to prevent participants walking outside of the constrained passage and the other is to set as reference for the automatic coordinate correction and calibration. In order to facilitate the trajectory extraction from the videos, the participants are asked to wear a white color safety helmet with the same size when they participate in each session. This idea was initially adopted by Daamen and Hoogendoorn [34] in their walking behavior experiments, then was also applied (with slight variation, e.g., participants are in clothes of particular colors rather than wearing the colored hats) by other research groups to facilitate the data collection process as well [164, 232].

13 students participated in all the experiment sessions, 4 females and 9 males. We randomized the selection of participants for each session from the “fast” and “slow” groups through initial training sessions. At the beginning of each session, two on-site coordinators randomly picked an algebraic calculation question from a set and presented the puzzle to participants just before they were told to move towards their goals. A total of 139 sessions were video recorded for the three scenarios over two weeks instead of on one or two consecutive days. Such an arrangement aims to avoid bias on movement patterns which may be caused by frequent repetition of scenarios.

Figure 7.2: Camera setup for the experimental studies.

According to the criteria (e.g., whether the simple algebra was calculated correctly; whether the participant from behind overtook the two in front within the area of interest in *Scenario Two*) as discussed above, we have selected 20 video clips for each scenario to further analyze in detail.

7.1.1.3 Data Collection and Extraction

Through the selected video clips, the coordinates of each participant along time are extracted to form the NXYT [204] data, which can be further analyzed to deduce information such as the speed and direction of participants at each time frame. The flowchart of the data collection and analysis process is summarized in Figure 7.3. The pre-processing was manually conducted as discussed above to select the video clips for in-depth analysis. The data extraction procedure through video processing is discussed in this subsection.

Figure 7.3: Flowchart of data collection and analysis process.

The overall data extraction through video processing was conducted in five steps as shown in Figure 7.3. For the first step of *video conversion*, we use the FFmpeg tool [16] to convert each video clip into an image sequence with frame rate of 20 *fps*, thus each frame has an interval of 0.05 s. This sampling interval ensures a sufficient resolution of the participants’ coordinates on consecutive video frames. The image sequences are then stored as ‘.tif’ files for further processing. We then use the imageJ software [167] with the MTrack2 plug-in [202] for the remaining four procedures.

After importing an image sequence in imageJ, the first step is *coordinate correction*. Because the image sequence is measured in pixel units by default in imageJ, it is necessary to convert to metric units. To do so, we first crop the image sequence according to the marker on the floor. The scale of the image is then set according to the recorded markers and the measured actual distance between these markers in the experiment field. In addition, we used image processing functions such as rotation and transformation, provided in imageJ, to fine-tune the coordinates for higher precision. The next step is *background subtraction*, through which we want to isolate the participants from the background. To achieve this objective, we first increase the contrast of the image sequence by 0.4%, then apply the built-in “background subtraction” function. The subtraction needs not be perfect as the binarization in the next step could further reduce the background noise. Next, *binarization* is applied to create significant difference between the information we need (i.e., the helmet on each of the participants) and the background noise. Binarization works depending on the

Figure 7.4: An example to demonstrate the data extraction procedures.

color and contrast of different areas in the image. We first split the color channels and pick the one with contrast between the helmet and the dress of the participants. For example, if the participant wears a blue dress, then the red channel will create more color contrast between the helmet and his body. Then we apply a threshold under the default algorithm in imageJ to obtain the binary image sequence in black and white. In this step, the single threshold may not always separate the helmet from other background noise perfectly, especially when sunlight or the light color dress of the participants impacts the process. *Manual correction* is then used to verify, adjust and correct the binarized image sequence. This process helps check the automatic binarized image sequence to make sure the helmet position of each participant in each frame is properly identified to facilitate the tracking process. In the last stage, we apply the multiple particle tracking algorithm using the MTrack2 plug-in on the binarized image sequences. This generates the XYT information of each participant

and outputs it to a text file. This plug-in is effective in tracking objects as particles. It allows the user to specify the minimal and maximum particle size, the minimal trajectory length and the maximum velocity of the objects in the image sequence; these parameters aid the plug-in in tracking multiple objects. Figure 7.4 demonstrates an example of the complete process in the video processing and data extraction.

7.1.2 Metrics to Measure

With the experimental data, the interactions among participants in different experimental scenarios can be analyzed through a set of metrics that are descriptive to reflect the interaction either from a qualitative categorization perspective or a quantitative measurement of the motion features of each participant.

7.1.2.1 Interaction Categories

(a) scenario one

(b) scenario two

(c) scenario three

Figure 7.5: Interaction categorization.

In the three scenarios, the interaction among participants can be categorized according to their relative positions throughout the session. Three categories can be observed

for Scenario One (see Cat1.1, Cat1.2 and Cat1.3 in Figure 7.5(a)), Scenario Two (see Cat2.1, Cat2.2 and Cat2.3 in Figure 7.5(b)) depending on whether the individual participant (2) avoids the other two through the space on their left or right-hand side, or at the middle of the two; two interaction categories can be observed in Scenario Three (see Cat3.1 and Cat3.2 in Figure 7.5(c)), depending on whether the individual participant (2) stays behind of the two in front moving in the narrow tunnel. Pedestrians' navigational behaviors are observed under different interaction categories with different frequencies in real life situations. We expect to find the frequency of different interaction categories under each scenario from our experiments. Interaction categories with different frequencies can help assess the facial validity of a simulation model. For instance, under similar scenarios, the simulation results of a model that produces the interactions with a high frequency appearing in the experimental data seem more realistic than models that always produce the rare interactions. In addition, quantitative analysis of the motion features of participants from multiple experimental sessions can be processed based on the interaction categories.

7.1.2.2 Preparation for Motion Feature Analysis

To further analyze the motion features of participants quantitatively, we use the collected NXYT data. Specifically, we examine the trajectories of each participant from different perspectives (metrics) quantitatively (e.g. moving speed, direction change along the trajectory) and the relationship of these metrics among the participants.

Under each interaction category, there are (probably) multiple experimental sessions recorded as demonstrated in Figure 7.6(a). For each participant's role (i.e., participant 1, 2 or 3), we measure the average trajectory of the participants in all the sessions under the same interaction category as demonstrated in Figure 7.6(b). The averaging operation is used mainly because of two reasons: First, the average trajectories and the smooth curves are good estimation of participants' smooth trajectories observed over all the sessions under the same interaction category. In the experiments, different participants enacting the same role in the scenario may have different motion features, thus generating slightly different trajectories. By averaging these different positions under the same interaction category, the average trajectory is representative to show the common steering behaviors of pedestrians in such a scenario. Secondly, the average trajectory of a participant helps neutralize and thus reduce the *noise* introduced in the *manual adjustment* procedure of the image processing step for data extraction. A rugged trajectory is generated from the MTrack2 particle

(a) tracked positions of all sessions

(b) average trajectories

(c) smoothed trajectories

Figure 7.6: Tracked and processed trajectories for motion feature analysis.

tracking algorithm [202] occasionally for certain sessions. The algorithm identifies the center of a particle (i.e., the position of a participant) through the average pixel color values. A slight variation in the adjustment will result in the biased tracked position for the participant at that particular time frame, thus to generate a slightly rugged trajectory. By averaging the positions of participants at the same frame over all the sessions, such noise can be reduced. The average trajectory is then fitted into a polynomial curve, which generates a smooth curve to represent the average trajectory as demonstrated in Figure 7.6(c). Trajectories are smoothed for further analysis mainly because of the *lateral swaying* and *jitters* observed in the average trajectories. The *lateral swaying* [109, 123] in participants' motion can be observed from the trajectories of participants in a particular session as shown in Figure 7.6(a). As an pedestrian moves forward step by step, the centroid of her body (reflected by the helmet the participants wore during the experiments) sways to the side of the foot stepping forward. Even with the averaging operation, the lateral swaying effect still exists in the average trajectories. To analyze the steering choices through the instantaneous changes of a participant's moving direction, the lateral swaying should be minimized. The polynomial fitting helps further reduce the *lateral swaying effect* from the average trajectories. The *jitters* are observed at the last segment of the average trajectories towards the destination. Such jitters are probably generated as the result of the position variances of different participants of the same role from different sessions. Such position variances are expected as a result of the accumulation of speed variances along time during the experiment. The polynomial fitting also helps reduce these jitters in the smoothed curves.

Through the averaging and smoothing process, the trajectories of participants under each interaction category are represented by the smooth curves. The subsequent quantitative metrics will be derived from the curves to measure the motion features of participants.

7.1.2.3 Metrics for Motion Feature Analysis

In order to quantitatively measure the motion features and interactions among participants, we propose to use the following metrics in this thesis:

- Trajectory length of participant i : L_i
- Maximum deviation distance of participant i : D_i
- Local slope of participant i at time t : lc_i^t

- Difference of local slope between participants i and j at time t : ΔLC_{ij}^t
- Separation distance between participants i and j at time t : d_{ij}^t
- Distance deviated from the horizontal direction line (along the x axis) of participant i at time t : dd_i^t
- Speed of participant i at time t : s_i^t

Figure 7.7: Metrics that are used to measure the trajectory of a participant.

The *trajectory length* L_i is calculated as the sum of distance over every 10 image frames, (i.e., given the frame rate of the image sequence as 20 fps, this period equals 0.5 s), which is an estimated time for one to move one foot forward. The *maximum deviation* D_i reflects how much deviation is made in the whole course of movement. It is measured as the largest distance to the horizontal direction line of the participant (i.e., along the x-axis as shown in Figure 7.7). In general, a longer trajectory length is associated with a larger maximum deviation distance. We will use these two metrics to summarize the overall trajectory of a participant.

The *local slopes* lc_i^t along a trajectory refers to the instantaneous change in moving directions between a participant's consecutive steps (i.e., the slope of the trajectory between the participant's steps). Its value is calculated as the tangent of the angle α_i^t from vector $\vec{V}_1$ (representing the participant's main moving direction along the x-axis) towards vector $\vec{V}_2$ (Figure 7.7). The difference of local slope ΔLC_{ij}^t between

participants i and j , is used to measure how different the deviation is between the two participants at time instance t . The analysis of the local slopes could reflect the steering choices in terms of the change in moving direction of a participant. The difference between their local slopes reflects how two participants interact with each other.

In addition to the measure of local slopes, the *deviation distance* dd_i^t of a participant, away from the horizontal direction line, and the distance between each pair of participants d_{ij}^t also reflect the interaction of the participants. The speed s_i^t of participant i at time t is an important metric to measure as well. s_i^t is calculated as the distance moved by the participant in a single frame. Frequent oscillations of the average speed is observed due to the relative high frame rate ($20fps$). Such oscillations indicate the lateral swaying in participants' natural gait. By averaging the speed of every 10 frames (i.e., 0.5 s), a smoothed average speed along time can be generated.

In the next section, we use the interaction category and the metrics proposed in this section to measure the interactions among participants in different scenarios.

7.1.3 Experimental Data Analysis

7.1.3.1 Interaction Categories

By examining the video clips collected for each scenario, the interactions among the three participants can be categorized into different categories as previously discussed. Figure 7.8 summaries the frequency of the observed interactions in the experiments under each category.

In *Scenario One*, it is noted that the single participant (participant 2) is much more likely to avoid the other two from either side (i.e., 95% of the sessions fall into Cat1.1 and Cat1.2). One possible reason for the higher probability of Cat1.1 and Cat1.2 over Cat1.3 is that the single participant is likely to perceive the other two as a group. Thus, she is most likely to avoid them from either side as shown in Cat1.1 and Cat1.2. There is a slightly higher probability for participants to avoid others from the left-hand side than the right-hand side (55% vs 40%). The difference is however insignificant with a p-value of 0.163 under the assumption that the probability of Cat1.1 is significantly (with a significance level of 0.9) higher than Cat1.2. The hypothesis test is detailed in Appendix C.

In *Scenario Two*, all the sessions fall into Cat2.1 and Cat2.2. Cat2.3 was not observed. In this set of experiments, the participant behind prefers to overtake from the left side (Cat2.1) (70% vs 30%). This difference may be due to the cultural bias of

Figure 7.8: Experimental statistics of participants' interaction under different interaction categories.

keeping to the left here in Singapore. This observation suggests that behavioral habits formed through social norms may affect the behaviors. However, a larger sample size would be needed to verify this.

In *Scenario Three*, only interactions under category Cat3.1 are observed from the data as participant 2 always follows behind. Since participant 2 was selected from the “fast” pre-screened group, she was expected to overtake, if the spatial configuration she perceived from the situation allows her to do so. However, due to the spatial constraints in the experimental scenario, there is not sufficient space in the narrow tunnel for her to overtake. Thus, she has to follow behind.

For each scenario, we measure the metrics deduced from our experimental data according to the interaction categories in the following subsections.

7.1.3.2 Scenario One Experimental Data

There are three interaction categories (i.e., Cat1.1, Cat1.2 and Cat1.3) observed from the experiments in this scenario.

Cat1.1

In Cat1.1, participant 2 avoids participant 1 and 3 from their left side. The average and the smoothed average trajectories of the 11 sessions under Cat1.1 are shown

in the Figure 7.9(a) and 7.9(b) respectively. The average trajectories are fitted to a six-degree polynomial curve with the goodness of fit, R^2 , indicated in the figure. The fitting method is chosen based on the good fit it has generated and the single expression of the curve.

(a) average trajectories

(b) smoothed trajectories

Figure 7.9: Trajectories of participants under Cat1.1.

Three main observations are made about the motion features of participants according to the metric measures. First, participant 2 deviates her route more than the other two (Figure 7.9). Such an observation can be quantized through the maximum deviation of different participants (see D_2 under Cat1.1 in Table 7.2) and the total length of the trajectories (see L_2). The observation from the experimental data is consistent with our observation in daily life situations, where smaller groups (or individuals) are more likely to avoid larger groups.

Secondly, the two participants with initial positions near each other (participant 1 and 3) exhibit strong correlations in their steering choices, in terms of both the

Table 7.2: Summary of participants' trajectories under different scenarios.

Metrics		<i>side-avoid</i> scenario			<i>overtake</i> scenario		<i>follow</i> scenario
		Cat1.1	Cat1.2	Cat1.3	Cat2.1	Cat2.2	Cat3.1
Max. Dev.	D_1	0.0785	0.3207	0.2412	0.0362	0.1269	0.0960
	D_2	0.8720	0.8684	0.3209	1.1544	0.7370	0.2558
	D_3	0.2656	0.1867	0.6575	0.1289	0.1112	0.0182
Traj. Len.	L_1	10.0542	10.1200	10.1507	6.2156	6.1189	6.1423
	L_2	10.238	10.2792	10.1593	12.5021	12.2383	9.9997
	L_3	10.1126	10.0789	10.1892	6.2468	6.0494	6.1025

moving speed and direction. The strong correlation in the trajectories of participant 1 and 3 can be also reflected from the perspectives of the distances between each pair of participants as shown in Figure B.3 and the deviation distance of each participant away from their horizontal direction lines as shown in Figure B.4. These metrics together imply that the steering choices of the two participants moving together are quite consistent and correlated.

Lastly, it is observed that all participants start to deviate relatively early (Figure B.4), even though their attention was deliberately shifted in the experimental protocol design. Such an observation is consistent with previous pedestrian studies, stating that pedestrians tend to start to avoid each other as far as 5 meters or at an even longer distance in a less dense situation [230]. Such a proactive steering behavior may suggest strategic planning in their cognitive processes as we have assumed.

Cat1.2

In Cat1.2, participant 2 avoids the other two from the right side. Similarly, we plot the trajectories of participants for Cat1.2 as shown in Figure 7.10. The maximum deviation D_1 , D_2 and D_3 , and the trajectory length L_1 , L_2 and L_3 for the three participants are summarized under Cat1.2 in Table 7.2. In this case, participant 2 deviates most and has the longest trajectory length.

For this interaction category, we have observed highly consistent motion features of participants as are observed in Cat1.1. The main difference is caused by the different deviation directions. In addition to the three observations we have drawn in Cat1.1, it may also indicate, from the data of Cat1.2, that the side-preference in participants' steering choices to avoid the oncoming collisions does not influence their motion features significantly. The readers are referred to Section B.1.2 in Appendix B for more details in the experimental data of this interaction category.

(a) average trajectories

(b) smoothed trajectories

Figure 7.10: Trajectories of participants under Cat1.2.

Cat1.3

In Cat1.3, participant 2 passes participant 1 and 3 from the space between them. Since only one session is observed under this category, the actual recorded trajectories of participants (Figure 7.11(a)) and the smoothed trajectories (Figure 7.11(b)) are shown in Figure 7.11. The maximum deviation D_1 , D_2 and D_3 , and the trajectory length L_1 , L_2 and L_3 for the three participants are summarized under Cat1.3 in Table 7.2. L_3 is the longest because participant 3 has the largest maximum deviation (see D_3).

In this interaction category, participant 2 avoided the other two in between, or a better way to describe the interaction should be that participant 3 initiated the interaction to avoid collisions through early deviation of his moving direction. Such an interaction is different from the previous interaction categories. The readers are referred to Section B.1.3 in Appendix B for more details in the experimental data of this interaction category.

(a) actual trajectories

(b) smoothed trajectories

Figure 7.11: Trajectories of participants under Cat1.3.

In summary, we have examined the motion features of participants for the three interaction categories observed in experiments of Scenario One. Participants exhibit quite similar interactions in Cat1.1 and Cat1.2, comparing with Cat1.3. Interaction categories Cat1.1 and 1.2 are observed with a much higher frequency than Cat1.3. We thus believe that such interactions indicate how participants are likely to perform in this scenario. Specifically, we have observed that participants in smaller groups (or individuals) tend to avoid the larger groups. Participants with similar initial positions and goals, steer in the similar way to avoid collisions, while maintaining their formation as a group. In addition, participants may adopt strategic planning in their movement to adjust their motion early with less change in speed and direction, but still trying to reserve personal space during collision avoidance.

7.1.3.3 Scenario Two Experimental Data

In this scenario, participant 2 overtakes participant 1 and 3 from either their left (Cat2.1) or right (Cat2.2) side. The same set of metrics are applied to measure the motion features of participants. Since the two interaction categories exhibit much similarities rather than the differences, experimental results of the two categories are presented together with the differences highlighted in this subsection.

Trajectories of the participants (both the average and the smoothed) are shown in Figure 7.12 and 7.13 respectively for Cat2.1 and Cat2.2. The star symbols indicate the location of participants when participant 2 has caught up with the other two participants and started to pass ahead of them. The average trajectory lengths, L and the maximum deviation D for the two categories are summarized under Cat2.1 and Cat2.2 in Table 7.2 respectively.

(a) average trajectories

(b) smoothed trajectories

Figure 7.12: Trajectories of participants under Cat2.1.

(a) actual trajectories

(b) smoothed trajectories

Figure 7.13: Trajectories of participants under Cat2.2.

From the trajectory plots and the tables, it can be observed that the single participant (participant 2) moving faster behind deviates to avoid collision with the two walking in front, who do not exhibit obvious deviation in their trajectories. Such interactions are different from Scenario One, where all the three participants react to each other actively. In this scenario, only participant 2 seems to proactively steer to avoid the other two. Such an interaction may be mainly due to the visual limitation of the participants walking in front. People usually do not react to others coming from behind until they are very close. The readers are referred to Section B.1.4 in Appendix B for more details in the experimental data of this scenario.

While some motion features observed in this scenario are similar to those observed in Scenario One (i.e., early deviation of participant 2 to avoid collisions; the larger deviation made by participant 2 than others), there are two unique differences observed in this scenario: First, the participant walking in the front seems to lack active

interaction with the participant coming from behind. Secondly, under no circumstances does participant 2 overtake the other two through the space between them, similar to Cat1.3 in the previous scenario. It may be reasonable to attribute such a difference in interaction to the visual constraints of participants as mentioned above. From this perspective, the vision and the visual perception of pedestrians is critical to their steering choices. Another interesting finding, related to the use of vision, can be drawn from the speed plots (Figure B.13 and B.14). The participants seem to be able to measure the distance and adjust their speeds to meet the objectives of the experiments well. In this scenario, participants were selected from the “fast” group to fill the role of participant 2. However, they were not told explicitly how fast they should walk and participants naturally have speed variances. From the experimental data, it is found that the speed ratio is almost 2:1 between participant 2 and the other two participants. The same ratio also holds for the trajectory lengths of these participants. Such observations could indicate that participants can perceive and cognitively assess the situation quite well and to adapt their actions accordingly.

7.1.3.4 Scenario Three Experimental Data

In this scenario, we observe only interaction type Cat3.1 for all the recorded sessions. Participant 2 remains behind participant 1 and 3 due to the spatial constraints. The average (Figure 7.14(a)) and the smoothed (Figure 7.14(b)) trajectories are shown in Figure 7.14. The star symbols on the smooth trajectories of participants in Figure 7.14(b) indicate their positions when participant 1 and 3 arrive at the destination ($X = 2$ m).

The average trajectory lengths, L and the maximum deviation D for participants are summarized under Cat3.1 in Table 7.2. The maximum deviation of participant 2 (see D_2) is the largest because she tends to follow behind participant 3 rather than to follow the two participants in the middle. This observation is consistent with the pedestrian study [230] as discussed previously. Nevertheless, it is noted that the overall curvature is relatively small for all the participants due to the spatial constraints deployed in this scenario.

The motion features of participants under this scenario share some similarities with those of Scenario Two. For example, participant 2 proactively adjusts her motion to avoid collision with the other two in front. Such an interaction is probably caused by the visual limitation of the other two in the front as discussed in the last scenario. A unique motion feature of participant 2 in this scenario is her preference for speed

(a) average trajectories

(b) smoothed trajectories

Figure 7.14: Trajectories of participants under Cat3.1.

reduction rather than direction deviation. This is possibly due to the perceived spatial constraint of the situation. The experiments in this scenario have also confirmed previous pedestrian studies by showing people's tendency to follow others slightly off-center (i.e., not directly behind) [54, 230]. More details on the experimental data of this scenario are discussed in Section B.1.5 in Appendix B.

Through the experimental studies across the three scenarios, we have several general observations on the movements of the participants listed as follows:

- Visually perceived constraints in a situation affect a pedestrian's steering behaviors.
- Pedestrians tend to perceive others with similar motion features as a group and interact with them as such.

- Pedestrians tend to adapt their motions early to avoid potential collisions with others.
- Individuals or pedestrians in a small group tend to avoid larger groups with greater effort in terms of the change in their speeds and directions.
- Pedestrians seem capable of measuring the environment well and adapting their motions effectively to achieve specific goals.

We believe such observations can be used to assess whether a simulation model can generate simulation results realistically under similar situations.

7.1.4 Comparison with Simulation Results

It is still a challenging topic to evaluate the realism of steering behaviors from a simulation model. Comparison is one of the most basic and common ways to measure the performance of different models. However, comparing the results of two different models is not a straightforward task. This is especially true when trying to discern which model is more human-like. In this section, we do not propose a measure of “humanness” for the behaviors of our model. The results and comparison are provided against the experimental data as discussed in Section 7.1.3. Our analysis is based on the set of metrics that were proposed to specify the motion features in the previous experimental study.

Specifically, we compare the simulation results of three models with the experimental data. This is done under the same set of test scenarios representing the three scenarios used in the experimental study. The three models include the proposed PBS model in this thesis, the RVO2 model (based on the RVO2 library [222] considering the personal space factor for more realistic virtual human behaviors as suggested in [60]), and the modified Social-Force model [113] for modeling human collision avoidance behaviors. The RVO2 model and the social force model are commonly used motion planning approaches for steering behavior simulation. The purpose of the comparison here is not to argue which is better or more efficient in generating collision-free steering behaviors. Instead, we want to demonstrate that the PBS model is capable of producing more human-like behaviors under a set of common situations. Essentially, we illustrate the facial and statistical validity of the PBS model.

In order to compare the simulation results with the experimental data, the initial conditions of the real scenarios are extracted and fed to the simulation models.

 (a) *side-avoid* scenario

 (b) *overtake* scenario

 (c) *follow* scenario

Figure 7.15: Initial setup of the simulation models based on the experimental studies.

Particularly, the initial positions (p_i) of agent Agt_i are set according to the initial positions of participants in the field experiments. The approximate average speed (s_i) of participant i in a scenario is set as the preferred speed of the agent in the model. The body radius r of an agent is set to 0.22m to estimate the average half body width of participants. To recreate the static obstacles (i.g., wall) used in Scenario Three, the obstacles are represented as line segments (O_i) as shown in Figure 7.15(c). The

Table 7.3: Summary of agents' trajectories in the PBS model under different scenarios.

		<i>side-avoid</i> scenario	<i>overtake</i> scenario	<i>follow</i> scenario
Max. Dev.	D_1	0.3156	0	0
	D_2	1.1220	1.4085	0.3808
	D_3	0.1675	0	0
Traj. Len.	L_1	10.0773	6	6
	L_2	10.2000	12.2264	8.7983
	L_3	10.0011	6	6

personal space factor (ρ) of agents affects the visual perception of the environment. A larger spatial area is perceived than the actual occupation of a person. We have calibrated these parameters as shown in Figure 7.15. With such settings, Agt_1 and Agt_3 are “close” to each other while still leaving certain space in between. Since the three scenarios are used to test the *side-avoid*, *overtake* and *follow* steering behaviors of agents, scenarios are named to be consistent with the steering strategies in this section.

7.1.4.1 PBS Simulation Results

In the simulation, we set the *commitment level* of all the agents as a random number between 0 and 1. Such a setting is to mimic the normal attention range of pedestrians during walking according to previous pedestrian studies [230]. Other parameters are set according to the experiment scenarios as shown in Figure 7.15. We replicate 20 simulation runs of the model for each scenario to account for the randomness introduced in the model and also to be consistent with the experimental data.

Side-avoid Scenario (Figure 7.15(a))

Through the 20 replications of simulation, we have found two types of interactions corresponding to the predominant (95%) interaction categories (Cat1.1 and Cat1.2) as observed in the experimental data. The simulated scenario is shown in Figure 7.16. The black color agents indicate that there is no steering strategy selected at that frame, and the blue color agents indicate the currently executing steering strategy is *side-avoid*. The dotted circle around an agent shows the personal space of the agent.

The trajectories of agents are shown in Figure 7.17. The average trajectory lengths, L and the maximum deviation, D are summarized under the *side-avoid* scenario in Table 7.3. It indicates that Agt_2 moves the longest trajectory due to its maximum deviation. This result is consistent with the experimental data.

Figure 7.16: The simulated *side-avoid* scenario in the PBS model. Figure 7.17: PBS model: the trajectories of agents under the *side-avoid* scenario.

The speeds of agents are shown in Figure 7.18. In general, the speeds of agents are fairly constant through the overall interaction process. The speed reduction of Agt_1 (see s_1) during frame 15 to 40 is interesting. Such speed reduction is caused by the locomotive velocity adjustment in the execution process of the *side-avoid* steering strategy. It can be observed from the screen-shot of the simulation (Figure 7.16(b)) that Agt_1 is trying to avoid Agt_2 from its left-hand side, while Agt_3 is currently on his left-hand side. The locomotive adjustment is performed on top of the steering strategy to slightly revise the actual velocity of the agent. This is arguably realistic as we also observe pedestrians behaving in similar ways when they come across each other in a corridor.

The distances between each pair of participants in this scenario is plotted in Figure 7.19. It shows that Agt_1 and Agt_3 maintain a relatively constant and close distance

Figure 7.18: PBS model: speeds of agents under the *side-avoid* scenario.

(see d_{13}) through the whole simulation. The shape and relative positions of the three curves (see d_{12} , d_{23} and d_{13}) are highly consistent with the experimental data in the corresponding interaction category (Cat1.1) (Figure B.3).

The deviation distances of agents from their horizontal direction lines are shown in Figure 7.20. All the agents start to deviate early to avoid collisions similar to the experimental data. Agt_2 has the largest deviation distance (see dd_2). Agt_1 and Agt_3 both keep a short deviation distance (see dd_1 and dd_3), while dd_1 is slightly larger than dd_3 because Agt_1 needs to deviate slightly more as shown from the trajectories in Figure 7.17. The local slopes of agents' trajectories are shown in Figure 7.21. It is observed that Agt_1 and Agt_3 have similar local slopes (see lc_1 and lc_3), which can also be reflected from the differences in local slope between the two agents (see ΔLC_{31}) in the same figure.

Figure 7.19: PBS model: distances between each two agents under the *side-avoid* scenario.

In summary, the PBS model reproduces simulation results that are highly consistent with the dominant interaction types (under Cat1.1 and Cat1.2 with 95% probability) of participants observed in the experiments. First, early deviation in the steering

Figure 7.20: PBS model: deviation distance from the horizontal direction line under the *side-avoid* scenario.

Figure 7.21: PBS model: local slope and the differences between each two agents under the *side-avoid* scenario.

behaviors have been achieved in the PBS model to reflect the strategic planning of pedestrians. In the PBS model, the concrete STP is formed and then triggers the side-avoid steering strategy in this case. Since the attention ranges are set dynamically according to the local density (or the nearest neighbor), the other two agents can be perceived in the ‘far’ attention range once they come within 14 m ($3.5m \times 4$). Such spatial constraints match with one of the prototypical STPs corresponding to the side-avoid steering strategy as discussed in Section A.3 of Appendix A.

Secondly, Agt_2 deviates to avoid the other two (Agt_1 and Agt_3) as a group. Agt_2 also avoids collisions with them proactively by deviating larger distance. Thirdly, Agt_1 and Agt_3 almost have the same steering choices to “side-avoid” the agent coming towards them from the same side. This is due to the similar perceived STP from the situation and the same matched prototypical STP that leads to the steering strategy. While in different simulation runs, an agent may choose to execute the side-avoid strategy from different sides of the perceived group. This also suggests that the perceived spatial configuration of the situation varies according to different vision

and attention ranges. Such variances in turn affect the formation of concrete STP and the execution of a particular steering strategy. We argue that such a mechanism naturally reflects pedestrians' implicit cognitive measurement of the situation.

Overtake Scenario (Figure 7.15(b))

Through the 20 replications of simulation, we have found two types of interactions corresponding to Cat2.1 and Cat2.2 in the experimental data. Due to the symmetric motion features of agents along their horizontal direction lines, we demonstrate the simulation result with one type only. The simulated scenario is shown in Figure 7.22. The black color agents indicate that there is no strategy selected at that frame, and the red color agents indicate the currently executing steering strategy is *overtake*.

Figure 7.22: Simulated *overtake* scenario in the PBS model.

The trajectories of agents are shown in Figure 7.23, which shows Agt_2 steers to overtake Agt_1 and Agt_3 from the left side, similar to the interaction under Cat2.1 as we have observed in the experiments (Figure 7.12). The trajectory lengths L and the maximum deviation D are summarized under the *overtake* scenario in Table 7.3. It indicates that Agt_2 has the longest path (see L_2) due to its largest deviation and the longest distance traveled along x-axis. One difference with the experimental data is that the maximum deviation of Agt_2 , D_2 is larger than the experimental data. Such a difference may be due to the static personal space factor we set for all the agents. In the simulation, the personal space factor of all the agents are estimated as 1.0 (Figure 7.15). We observe that the participant overtaking from behind gets very close to the target once she catches up. At such a distance, the personal space of both participants should be very small. However we have not considered this dynamic

change of the personal space factor in the current model. Further refinement of the model (to set this factor according to the perceived local density) could improve the robustness of the model so as to address this issue.

Figure 7.23: PBS model: trajectories of agents under the *overtake* scenario.

Figure 7.24: PBS model: local slope and the differences between each two agents under the *overtake* scenario.

Figure 7.25: PBS model: speeds of agents under the *overtake* scenario.

It is also observed that Agt_1 and Agt_3 has an identical local slope of value 0 (see

lc_1 and lc_3 in Figure 7.24), which is consistent with the observation drawn from the experiments that the two in the front do not react to the one coming from behind. The speeds of agents are plotted in Figure 7.25. The speeds of the two agents in the front (s_1 and s_3) are constant through the whole simulation due to their lack of active interaction with the other agent. The speed of Agt_2 (s_2) starts to increase gradually until frame 57, which reflects the “catch-up” phase in the execution process of the *overtake* steering strategy. The speed variation of agents in the simulation is generally consistent with participants’ speeds observed in the experimental data, where s_2 increases during the overtaking process and s_1 and s_3 remains constant.

Figure 7.26: PBS model: distances between each two agents under the *overtake* scenario.

Figure 7.27: PBS model: deviation distance from the horizontal direction line model under the *overtake* scenario.

The distances between each two agents in this scenario are shown in Figure 7.26. It is observed that Agt_1 and Agt_3 maintain a consistent and close distance (see d_{13}) through the interaction process as we have observed in the experimental data. The distances between agents d_{13} , d_{23} and d_{12} , and their changing pattern along time

are similar to the experimental data as well. The deviation distances of agents are plotted in Figure 7.27. Except for the slightly larger deviation distance of Agt_2 (see dd_2), the plot is again consistent with the experimental data. In summary, the PBS model reproduces simulation results which are highly consistent with the behaviors of participants as observed in the experimental data.

Follow Scenario (Figure 7.15(c))

Through the 20 replications of simulation, we found all simulation runs produce the type of interactions corresponding to the interaction category Cat3.1 in the experimental data. The simulated scenario is shown in Figure 7.28. The black color agents indicate that there is no strategy selected at that frame, and the yellow color agents indicate the currently executing steering strategy is *follow*.

Figure 7.28: Simulated *follow* scenario in the PBS model.

The trajectories of agents up to frame 135 (when Agt_1 and Agt_3 cross the destination at $x=2$) are shown in Figure 7.29. Agt_2 remains behind Agt_1 and Agt_3 , similar to the interaction we have observed in the experiments. Note that Agt_2 randomly chooses to follow either Agt_1 or Agt_3 as specified in the model. Figure 7.29 demonstrates one simulation session where Agt_2 follows to the side of Agt_3 . The trajectory lengths L and the maximum deviation D are summarized under the *follow* scenario in Table 7.3. It indicates that the overall curvature of all the agents (see D_1 , D_2

 Figure 7.29: PBS model: trajectories of agents under the *follow* scenario.

and D_3) are relatively small while D_2 is the largest, which is also observed from the experimental data.

 Figure 7.30: PBS model: local slopes of agents' trajectories and the differences between each two agents under the *follow* scenario.

The local slopes of each agent and their differences between each pair of agents are shown in Figure 7.30. In general, similar patterns of lc and ΔLC are observed as of the experimental data. However, there are differences. First, there is absolutely no curvature generated in the trajectories of the two agents in the front (see lc_1 and lc_3) as the lateral swaying is not considered in the model. Besides, Agt_2 starts to deviate towards Agt_3 early (see lc_2), which is different from the experimental data (Figure B.22). As such, the maximum absolute local slope of 0.2 in the simulation result is smaller than 0.35 of the experimental data. These differences suggest that pedestrians could maintain a smaller deviation angle if they deviate early. Since the PBS model is based on the assumption that pedestrians would apply strategies as soon as they perceive certain spatio-temporal patterns, the early deviation of Agt_2 is achieved in this test case. Such an implementation of the execution process of the follow steering

strategy is consistent with the previous pedestrian studies [230], which states that pedestrians tend to adapt their motion early to avoid collisions with others. The difference with the experimental data could be due to the relatively small sample size of our experimental data.

Figure 7.31: PBS model: speeds of agents under the *follow* scenario.

The speeds of agents are plotted in Figure 7.31. The speeds of the two agents in the front (s_1 and s_3) are constant through the overall interaction process due to the lack of reaction with Agt_2 . We observe three different phases of speed change in s_2 corresponding to the phases of the steering strategy as shown in Figure 7.28. From frame 0 to 10, s_2 remains at the initial speed of $1.75m/s$, indicating there is no strategy involved. Between frame 11 and 147, it starts to decrease gradually, as Agt_2 reduces its speed to approach to the perceived group in the front. The speed reduces quickly from frame 148 to 181 because the agent is matching its own velocity with the target to follow. From frame 182 onwards, s_2 reduces even faster because it needs to match with s_3 in a very short distance. Such a speed change in the simulation is similar to the experimental data. In addition, it also shows that the model considers the subtle quantitative relation of speeds and the headway distance between the agent and other agents in front (Agt_3 in this case) as suggested in [185].

The distances between each pair of participants in this scenario are shown in Figure 7.32. The plots are consistent with the experimental data, except that the distance between Agt_1 and Agt_2 (see d_{12}), and Agt_2 and Agt_3 (see d_{23}) reduce faster from frame 148 onwards due to the speed changes as discussed above. Agents' deviation distances from the horizontal direction lines are shown in Figure 7.33. d_2 is larger than d_1 and d_3 , which are constant along time. This indicates the non-reactive movement of Agt_1 and Agt_3 as observed in the experimental data.

Figure 7.32: PBS model: distances between each two agents under the *follow* scenario.

Figure 7.33: PBS model: deviation distance from the horizontal direction line under the *follow* scenario.

Through the comparison between the simulation results of the PBS model and the experimental data, we have demonstrated that the simulation results from the PBS model are quite consistent with what we have observed from the experimental data, both in terms of the interaction categories and the metrics that are used to quantitatively measure the motion features of the agents.

7.1.4.2 RVO2 Simulation Results

From the modeling point of view, the main difference of the PBS model and the RVO2 model lays in the preferred velocity generation. The preferred velocities are generated as procedural instruction to execute a steering strategy through the pattern-matching process in the PBS model. In RVO2 (and the social force model as will be discussed), the preferred velocity is set as the vector towards the destination with small perturbation (i.e., $\epsilon = 5 \times 10^{-5}$), and the magnitude is set at some preferred speed of the agent. The initial conditions such as the initial positions, preferred speeds and the personal space factors for all the agents are set according to the setup conditions

Table 7.4: Summary of agents' trajectories in the RVO2 model under different scenarios.

		<i>side-avoid</i> scenario	<i>overtake</i> scenario	<i>follow</i> scenario
Max. Dev.	D_1	0.3860	0.3823	0.1955
	D_2	0	1.4085	0
	D_3	0.3860	0.3823	0.1955
Traj. Len.	L_1	10.6840	6.4332	7.0456
	L_2	10.0150	11.9419	11.8310
	L_3	10.6840	6.4332	7.0456

as shown in Figure 7.15. The parameters τ and τ' (for static obstacle) of the RVO2 model are set as $2s$ (i.e, $40\times$ frame rate) and $0.05s$ respectively as suggested in [222].

Side-Avoid Scenario

All the 20 replications of simulation results generated from the RVO2 model belongs to the interaction category Cat1.3, where the individual agent Agt_2 passes the other two through the space in the middle of them. This is a rare interaction (5%) observed from the experimental data.

The simulated scenario is shown in Figure 7.34. It is observed that Agt_1 and Agt_3 start to deviate to both sides early at frame 23 (Figure 7.34(b)) according to the time horizon parameter (τ). The agents complete collision avoidance at frame 72 (Figure 7.34(d)) and resume their velocities towards their goals at frame 73 (Figure 7.34(e)). During the interaction process, different agents adjust their motion in different ways. Agt_1 and Agt_3 deviate their directions while Agt_2 reduces its speed to avoid collisions.

Trajectories of the agents are shown in Figure 7.35. The trajectory lengths and the maximum deviation are summarized under the *side-avoid* scenario in Table 7.4. Agt_1 and Agt_3 deviate significantly (see D_1 and D_3) to avoid collision with Agt_2 . As a result, the trajectory length L_1 and L_3 are longer than L_2 . More details of the simulation results and corresponding discussion is provided in Section B.2.1.1 of Appendix B.

An important observation from the simulation results of the RVO2 model is the perfect symmetric characteristics in the motion of Agt_1 and Agt_3 . It can be reflected from the distances between each two agents as shown in Figure B.27, where the distance between Agt_1 and Agt_2 (d_{12}), and the distance between Agt_2 and Agt_3 (d_{32}) are perfectly identical along the whole moving course. Such a perfect symmetry is hardly observed in the experimental data. The author believes that the major reason

Figure 7.34: Simulated *side-avoid* scenario in the RVO2 model. Figure 7.35: RVO2 model: trajectories of agents under the *side-avoid* scenario.

for the symmetric behaviors of the RVO2 model in such a test case is the perfect cooperative assumption made by the RVO2 algorithm. Under such an assumption, each of the paired agents in the calculation is assumed to adjust her velocity by half to achieve a collision free paths between them [222]. The symmetry can be also reflected from the deviation distance from the horizontal direction line of each agent (Figure B.28) and the local slope and their differences between each two agents

(Figure B.26). Although a collision-free path for each agent can be generated through the symmetric cooperation among agents, it has its drawbacks. As discussed in [135], theoretical issues on the superposition of pair-wise interactions in the RVO2 model poses a challenge. In addition, we argue that such perfect symmetric behaviors hardly represent realistic pedestrian motion that is observed in both the experiments and daily life situations.

In this scenario, the RVO2 model reproduces an interaction that is rarely observed in the experimental data. There are also differences in motion features, although smooth trajectories and behaviors of agents are generated by this model.

Overtake Scenario

The interaction of the three agents is under interaction category Cat2.3, which was not observed in the experimental data for this scenario. In the experiments, participant 2 overtakes the other two either from the left or right side, but Agt_2 goes through the middle of the two agents in the simulation. The simulated scenario is shown in Figure 7.36. Agt_1 and Agt_3 starts to deviate to both sides at frame 61 (Figure 7.36(b)). At frame 124 (Figure 7.36(d)), the collision avoidance steering behaviors are completed, the three agents resume their velocities towards the goal at frame 125 (Figure 7.36(e)).

Figure 7.36: Simulated *overtake* scenario in the RVO2 model.

The trajectories of agents are shown in Figure 7.37. The trajectory lengths and the maximum deviation are summarized under the *overtake* scenario in Table 7.4. The trajectory lengths are slightly longer than the experimental data for all agents in this case. It is because that when Agt_1 and Agt_3 reaches at position with $x = 2$, Agt_2 has not caught up with them yet due to its slight speed reduction as shown in Figure B.30. To demonstrate the complete interaction, more frames are counted in this case until Agt_1 and Agt_3 are overtaken by Agt_2 .

Figure 7.37: RVO2 model: trajectories of agents under the *overtake* scenario.

In this scenario, a completely different interaction is observed from the simulation results of the RVO2 model compared with the experimental data. The motion features of agents in terms of the speed and directional changes are inconsistent with the experimental data¹. We have shown from the results that RVO2 may generate artificial results at low densities although it is often applied for collision avoidance and crowd simulation in scenarios with higher densities.

Follow Scenario

The simulated scenario is shown in Figure 7.38. The simulation results belong to the interaction category Cat3.2, which was not observed in the experiments. In the simulation, Agt_2 goes through the middle of the two agents in the front. The same interaction is observed in this scenario as we have observed in the *overtake* scenario, despite the different spatial constraints (static obstacles) in the scenarios.

It is noted that the personal space factor ρ contributes to the interaction and trajectories of agents in this case. By increasing ρ to a larger value (e.g., $0.5(\times r)$), Agt_2 can not surpass the two agents in the narrow corridor. However, the motion features of agents are still quite different from the experimental data even with the increased

¹Since no experimental data is observed under Cat2.3, we refer to the corresponding metrics of experimental data under Cat2.1 and Cat2.2

Figure 7.38: Simulated *follow* scenario in the RVO2 model with the default $\delta (=0.35)$.

Figure 7.39: Simulated *follow* scenario in the RVO2 model with increased $\delta (=0.5)$.

ρ value. As demonstrated in Figure 7.39, Agt_1 and Agt_3 still deviate sideways until they are constraint by the wall at frame 100 (Figure 7.39(d)), while Agt_2 continues

to move forward. The speeds of Agt_1 and Agt_3 are then forced to increase to the same as Agt_2 and remain afterwards (Figure 7.39(e) and Figure 7.39(f)). Although such an interaction is similar to the experimental data (Cat3.1), the motion features of agents are quite different. In the simulation of the RVO2 model, the Agt_1 and Agt_3 actively adjust their motion (in both speed and direction), whereas participant 1 and 3 in the experiments lack such proactive interaction. Instead, participant 2 adapts her motion to follow behind. The discussion here is to supplement the discussion on the simulation results of the RVO2 model under this scenario. However, the metrics are measured from the simulation results, with the same ρ value of 0.35, for the purpose of model comparison under the same setup condition.

Figure 7.40: RVO2 model: trajectories of agents under the *follow* scenario.

The trajectories of agents are shown in Figure 7.40. Trajectory lengths and the maximum deviation are summarized under the *follow* scenario in Table 7.4. Similar trajectories are observed in this scenario when compared to the trajectories of agents in the *Overtake* Scenario, except for the slight difference in the maximum deviation made by Agt_1 and Agt_3 (see D_1 and D_3). In this scenario, D_1 and D_3 are smaller than their values in the *Overtake* Scenario because of the smaller personal space factor value. Comparing the metric measures in this scenario with the previous scenario, it suggests that the RVO2 model generates quite similar behaviors under the two different scenarios, which are inconsistent with the experimental data. The author note that by imposing a limited vision range for the two agents in front, a different interaction can be generated in this case from the previous 'overtake' scenario. Under this case, Agt_2 can not overtake the two in front, but keeps moving close to them until it is within a short distance. It will then reduce its speed significantly in this process to avoid potential collisions. Such a passive 'follow' behavior is also different from the proactive 'follow' behavior as observed in the experiments.

Table 7.5: Summary of agents' trajectories in the social force model under different scenarios.

		<i>side-avoid</i> scenario	<i>overtake</i> scenario	<i>follow</i> scenario
Max. Dev.	D_1	0.5111	0.3832	0.2954
	D_2	0.0001	0	0.0456
	D_3	0.5112	0.3834	0.2050
Traj. Len.	L_1	10.1560	7.0344	7.0654
	L_2	9.7923	12.6667	10.3182
	L_3	10.1560	7.0344	7.2548

In summary, simulation results from the RVO2 model indicates symmetrically cooperative interactions among all the three agents within a distance defined by the time horizon parameter. Such steering behaviors are generated by the single optimal motion control mechanism regardless of the situations. From the modeling point of view, such a mechanism can be computationally efficient for collision avoidance through linear programming. However, it highlights a potential problem of the lack of adaptation for the model, i.e. it fails to produce similar steering behaviors of pedestrians in several common situations (scenarios) as observed in the experiments.

7.1.4.3 Social Force Simulation Results

Side-Avoid Scenario

Through 20 replications of simulation, all the simulation results from the Social Force (SF) model belongs to Cat1.3, where the individual agent Agt_2 passes the other two from the space between them, which is consistent with the RVO2 simulation results, but a rare interaction type (5%) observed in the experimental data.

The simulated scenario is shown in Figure 7.41. Agt_1 and Agt_3 are repulsed away from the initial position at frame 1 (Figure 7.41(b)). When getting closer, Agt_1 and Agt_3 deviate sideways while Agt_2 reduces its speed (Figure 7.41(c)) to avoid collisions. Trajectories of the agents are shown in Figure 7.42 and the trajectory lengths and the maximum deviation are summarized under the *side-avoid* scenario in Table 7.5. Agt_1 and Agt_3 deviate significantly (see D_1 and D_3), while Agt_2 reduces speed to avoid collisions (see the more dense points on the trajectory of Agt_2). As a result, L_1 and L_3 are longer than L_2 . The overall interaction is quite similar to the simulation results of the RVO2 model except that the collision-avoiding behaviors of the three agents only occur right before the invasion of their personal space in this model.

Figure 7.41: Simulated *side-avoid* scenario in the social force Model. Figure 7.42: Social Force model: trajectories of agents under the *side-avoid* scenario.

A common characteristic between the RVO2 and the SF model is that the actual velocity of an agent that avoids collision with other agents is calculated against each of the agents in a sequential manner. Therefore, the final velocity is set as the velocity that excludes any velocity that leads to potential collisions with any of the agents. Such superposition of pair-wise interactions generates unrealistically “perfect” motion of agents for collision avoidance. This is rarely observed from the experimental data or real life situations.

Overtake Scenario

The simulated scenario is shown in Figure 7.43. The interaction of the three agents in these results is under Cat2.3, which is not observed in the experimental data. It can be seen from Figure 7.43(c) that Ag_{t1} and Ag_{t3} deviate sideways to avoid collision with Ag_{t2} .

Figure 7.43: Simulated *overtake* scenario in the social force model. Figure 7.44: Social Force model: trajectories of agents under the *overtake* scenario.

The trajectories of agents are shown in Figure 7.44. The trajectory lengths and the maximum deviation are summarized under the *overtake* scenario in Table 7.5. In this scenario, the simulation results of the SF models are again very similar to the simulation results of the RVO2 model except that the adjustment of agents' motion starts later in the SF model than in the RVO2 model. The affecting range of forces are limited in the SF model, while the reacting distance is modeled as a time-related factor through the time horizon parameter in the RVO2 model. Compared to the experimental data, the SF model generates quite different results.

Follow Scenario

The simulated scenario is shown in Figure 7.45. The interaction of the three agents in these simulation belongs to the interaction category Cat3.1, which is consistent with the experimental data.

Figure 7.45: Simulated *follow* scenario in the social force model.

Figure 7.46: Social Force model: trajectories of agents under the *follow* scenario.

The trajectories of agents are shown in Figure 7.46. Trajectory lengths and the maximum deviation are summarized under the *follow* scenario in Table 7.5. *Bounces* are observed between Agt_3 and the wall when Agt_2 approaches it. Because of such bounces, L_3 is larger than L_1 , even though D_3 is smaller than D_1 . Such bounces are caused by the repulsive force between the agent and the static obstacle. By tuning

the parameter values in the repulsive force formulae, such bounces can be minimized, but with the potential disadvantage of failing to avoid collision with the wall. The fine tuning of parameter values in this case is critical to achieving a balance between the natural smooth motion of agents and the effectiveness in their collision avoidance. It is thus a great challenge to set these parameters accurately to accommodate different scenarios, though various ways such as the evolutionary computation techniques [92] are used for this purpose. This is a well recognized problem [160] of the SF model.

In this scenario, different motion features (measured through the metrics) are observed from the simulation results of the SF model, when compared with the experimental data, although the interaction of agents belongs to the same category of the experimental data.

7.1.4.4 Summary

The comparison between the simulation results and the experimental data does highlight that the PBS model is capable of producing different behaviors (more consistent with the experimental data) in several common real-life situations as expected, when compared to the other two motion planning models. Through such experimental and comparison studies, we tried to establish the facial validity and statistical validity of the PBS model in generating more realistic and consistent results under the set of selected scenarios.

In the PBS model, agents adopt different steering strategies according to the different perceived constraints of the situation. In this study, three different scenarios are used to demonstrate the three commonly observed steering strategies of pedestrians. The PBS model generates much more close simulation results to the experimental data than the other models in all three scenarios. Firstly, agents with similar initial positions and goals behave in a similar way (Agt_1 and Agt_3). Secondly, all the agents apply the steering strategies proactively as soon as they perceive corresponding spatio-temporal patterns. Such strategic movements replicate the early adaptation of their motion as observed in participants' movement in the experiments. Lastly, the agents with similar motion features are perceived as a group and other agents interact with the perceived group rather than individuals separately. Although RVO2 and SF models can be modified (e.g. cognitive module is added in RVO2 to allow group perception as reported in [224]) to incorporate such cognitive features, the PBS model naturally supports such features. Through successfully replicating these observed motion features of the participants, it demonstrates that the PBS is capable of

generating various steering behaviors realistically to mimic the real pedestrians. This is a significant difference and improvement from the traditional motion planning algorithms, where agents' motion are planned through a single optimal solution, but lack of correlation with pedestrians' steering behaviors as observed in real life situations and as demonstrated in the experimental studies.

7.2 More Complex Scenarios

7.2.1 Motivation

Through the controlled experiments and the comparison studies of different models against the experimental data, we have examined the PBS model thoroughly with various metrics in section 7.1 and demonstrated that the model is capable of modeling pedestrians' steering behaviors realistically in the set of selected scenarios. To apply the PBS model for pedestrian simulation, the model needs to be tested and validated using more complex and general scenarios.

As discussed in Chapter 6, it is challenging to assess the simulation results of a model in a complex scenario. Various test cases were widely applied to evaluate the simulation results through a set of aggregated level of crowd features. These crowd features emerge from the complex interactions of individuals and are recognized as important benchmarks to evaluate the simulated crowd behaviors [59, 61, 134, 148]. Such crowd features can be assessed subjectively by the SMEs, or quantitatively through a set of metrics. For example, a well recognized crowd phenomenon, the *lane formation* [54] is argued to be intuitive and reflective of realistic crowd motion in a counterflow scenario. A model can be assessed through the simulation results to spot whether the lane-formation phenomenon are produced (qualitatively) [25, 70, 110, 201]. For other researchers, they believe that smooth and cooperative motion among individuals in the crowd is driven by the tendency of pedestrians to minimize their effort and energy according to the *angular minimization* rules [49, 54] and the *least effort* theory [246]. Accordingly, metrics such as effort and energy were applied to quantitatively evaluate the collective efficiency of a crowd simulated by a model [59, 97, 174].

Pedestrians exhibit different aggregated steering behaviors in different scenarios. Therefore, different evaluation methods should be applied to test a simulation model under different scenarios. In this section, we adopt commonly used simulation scenarios from existing work that involve more complex crowd interactions to test the

PBS model further. There are two main goals in this part of validation work. First, we want to show that the PBS model can be used to simulate collective effects and self-organization encountered in pedestrian dynamics under different complex scenarios. This helps validate the model functionally. Secondly, we also show that the PBS model can perform comparatively well in scenarios, where the current set of steering strategies defined in the model are not triggered. This indicates that the pattern-based approach is robust and the model is capable of modeling both the strategic and non-strategic motion of pedestrians realistically. For evaluation purposes, we compare the simulation results through model alignment of three models, PBS, RVO2 and SF models.

7.2.2 Scenarios Design

Previous work in steering behavior and crowd simulation use different scenarios to test their models [97, 106, 148, 160, 162, 196]. It is interesting to find that these scenarios can be categorized into different groups based on the number of *main motion axis* (*mma*) involved in the scenario. By *mma*, we refer to the axis, which is parallel to the main moving directions of pedestrians (formed from their initial position towards the goal) as shown in Figure 7.47. The most common scenarios are “unidirectional” [75] and “bidirectional” [25, 134, 232] scenario, where the number of *mma* equals to one. The number of *mmas* involved in a scenario is usually defined and constraint by the virtual environment. For instance, in a corridor or hallway virtual environment, there is usually only one *mma* involved. The number of *mmas* involved in a scenario affects the aggregated motion of the crowd, and thus results in different pedestrian dynamics. Therefore, we categorize the commonly used test scenarios for crowd behaviors according to the number of *mmas* involved in the scenario. Particularly, scenarios with one (see 7.47(a)), two (see 7.47(b)), and n ($n \geq 3$) (see 7.47(c)) *mmas* are used to test the simulation models in this thesis.

7.2.2.1 Corridor (with one *mma*)

When there is one *mma* in the scenario, a typical test scenario is a corridor, where unidirectional or bidirectional flow of pedestrians emerges. Such a scenario was extensively used in almost every piece of work on pedestrian simulation [59, 97, 148, 162, 176, 201, 212], and is included as one of the fundamental scenarios in the benchmark test scenario set proposed in [196]. Specifically, we use two corridor scenarios to test the PBS model as shown in Figure 7.48. In the first scenario (Figure 7.48(a)),

Figure 7.47: Categorization of complex scenarios according to the number of *mma* involved.

Figure 7.48: The *corridor* test scenarios.

a narrow corridor (5 m wide) with spatial constraint (3 m wide) in the middle is adopted from Still's work [201] to test the unidirectional flow of a massive crowd of 200 agents. The crowds move from the left to the right side of the corridor. This scenario is mainly used to test various crowd phenomena from the simulation. The second corridor scenario (see 7.48(b)) is used to statistically validate and compare models with various metrics to reflect the motion features of agents. In this scenario, the corridor is 35 m in length and 5 m in width. 16 agents are initiated at each end of the corridor with the identical distance of 1m away from each other. Their main moving direction is parallel to the corridor. A simulation run is completed when all the agents have crossed the border at the destination side, or when the simulation has reached 1000 simulation steps. This is a much longer-than-expected simulation time to complete the simulation under this scenario used to avoid the deadlock situation, which occasionally occurs for some models.

7.2.2.2 Cross (with two mmas)

When there are two mmas, a typical test scenario is a cross situation. Such a scenario was also used in many previous work such as [59, 148, 201], and is also included as one of the fundamental scenarios in the benchmark test scenario set [196]. We set up

Figure 7.49: The *cross* test scenario.

a cross scenario as shown in Figure 7.49. The vertical and the horizontal corridor is 30 m in length each and 5 m in width. 16 agents are initiated at the top and right end of the corridors with the identical distance of 1 m away from each other. Instead of defining the main direction for the agents, we set specific goal position and an intermediate way-point at the cross for each corridor. Agents always move towards their predefined goals located at the other end of the corridor when they can sense them (through vision). In the case where an agent's vision is blocked by a wall to detect its goal, the intermediate waypoint will become the temporary goal and the agent moves towards the waypoint until it can sense the goal again. A simulation run is completed when all the agents have reached their goals, or when 1000 simulation steps have been reached.

7.2.2.3 Circle (with 16 mmas)

When there are many mmas in the scenario, a typical test scenario is a circle, where each agent tries to reach the other end of the diagonal on the circle as shown in Figure 7.47(c). Such a scenario was also used in previous work with different number of agents to form the circle [59, 148, 219, 221]. Without losing generality but still being able to make a complex scenario, we use a scenario with 32 agents as shown in Figure 7.50. The number of mma is 16 in this scenario. The diameter of the circle is 30 m. The 32 agents are evenly distributed around the circle during initialization.

Figure 7.50: The *circle* test scenario.

A simulation run is completed when all the agents have reached their goals (which are set at the other end of the diagonals from their initial positions), or when 1000 simulation steps have been reached.

In all three scenarios, the parameters for each model are set the same as used in the experiment under the “Side-Avoid” scenario (see Section 7.1.4.1), except the personal space factor. In these scenarios, this parameter is set to 0.3, which is smaller than the value of 1 used in the previous scenarios. This is due to the fact that the density of the simulated crowd in these scenarios is larger than the previous scenarios.

7.2.3 Criteria to Measure

Both qualitative emerging crowd phenomena and quantitative metrics of the crowd, which have commonly been used for validation of a crowd simulation model in the previous work, will be assessed and measured.

To facially validate a model, one can judge the simulation result alone to determine whether the results are reflective of natural movements of pedestrians, or one can investigate on the model’s capability of generating well-known emerging crowd phenomena that have been reported in the previous pedestrian studies. Some commonly crowd phenomena as summarized in [59, 69, 201] include lane formation, edge effect, wake effect, swirling, unevenly distributed density. These phenomena can be tested in narrow corridor scenarios as shown in Figure 7.48.

Facial validation on the qualitative crowd phenomena is not sufficient to validate a model as discussed previously. We also compare the models on several quantitative metrics that have been frequently used in the previous work. Below is a list of such metrics with brief descriptions adopted from several previous studies [49, 59, 97, 196]. Some of these metrics are the same as used in the experimental study as discussed in Section 7.1 to reflect the motion features of agents, while others are adopted from previous studies to measure other aspects of crowd dynamics such as their collective efficiency. Such metrics were argued being reflective of various characteristics of a crowd in common situations.

- T : completion time of all agents to complete a simulation run in terms of number of frames (frm)
- L : total trajectory length of all agents (m)
- D : total vertical deviation distance by all agents (m)
- $\sum \Delta|V|$: speed change by all agents (m/s)
- a : average acceleration per agent (m/s²)
- $\sum \Delta|A|$: direction change by all agents (°)
- α : average angular acceleration per agent (°/s²)
- E : total biomechanical energy spent by all agents (J)
- E_s : total biomechanical energy by steering caused by the steering behaviors of all agents (J)
- I : total inconvenience caused (agts)
- $\bar{I}$: average inconvenience per frame (agts/frm)

T is measured as the number of frames to finish the simulation. A shorter time to finish the simulation may indicate a more efficient emerging motion patterns of the agents. L is calculated as:

$$L = \sum_{i=0}^T \sum_{j=0}^N |v_j^i| t_0, \quad (7.1)$$

where t_0 (simulation time step) is set as 0.05 s in this experiment; v_j^i is the actual velocity of the agent j at frame i in the simulation; N is the number of agents.

D is the aggregated deviation distance steered by all the agents perpendicular to their main moving direction along an mma , and is calculated as:

$$D = \sum_{i=0}^T \sum_{j=0}^N |v_j^i| \cos \theta_i t_0, \quad (7.2)$$

where θ_i is the angle between the actual velocity v_j^i of agent j at frame i and the corresponding mma . A larger value of D indicates a longer deviation distance of the agents, thus to likely result in a longer total distance L .

$\sum \Delta|V|$ and $\sum \Delta|A|$ are calculated as:

$$\sum \Delta|V| = \sum_{i=1}^T \sum_{j=0}^N ||v_j^i| - |v_j^{i-1}||. \quad (7.3)$$

$$\sum \Delta|A| = \sum_{i=1}^T \sum_{j=0}^N \cos^{-1} \left(\frac{v_j^i \cdot v_j^{i-1}}{|v_j^i| |v_j^{i-1}|} \right) \cdot \frac{180}{\pi}. \quad (7.4)$$

a and α are then calculated as:

$$a = \frac{\sum \Delta|V|}{NTt_0}. \quad (7.5)$$

$$\alpha = \frac{\sum \Delta|A|}{NTt_0}. \quad (7.6)$$

The metrics above reflect the collective motion features of all the agents. In addition, we also measure the “collective efficiency” of agents in a simulation run. From the previous studies, it is noted that the efficiency of a crowd can be measured through both the physical (biomechanical) and cognitive effort all the individuals have made in the moving process. As suggested in [59], the biomechanical energy E spent by all the agents is calculated as:

$$E = \sum_{i=0}^T \sum_{j=0}^N \left(e_s + e_w |v_j^i|^2 \right) m, \quad (7.7)$$

where e_s and e_w are the constants with the empirical values of $2.23J/Kgs$ and $1.26Js/Kgm^2$ for an average human [227]; m is the mass of a virtual pedestrian, and it is set as 70 kg for all agents in the simulation. From equation 7.7, it can be inferred that the total energy E is determined by the actual speed of all the agents over time. In order to measure the energy cost by the steering behaviors of the agents,

which is a more indicative metric to show the steering effort, we use the metric E_s , which is calculated as:

$$E_s = \sum_{i=1}^T \sum_{j=0}^N (e_s + e_w |v_j^i - v_j^{i-1}|^2) m. \quad (7.8)$$

To measure the cognitive effort that is involved in the decision-making process of pedestrians, we adopt a metric called *inconvenience* I from [224]. I is measured as the number of agents who choose an actual velocity other than its preferred velocity. i.e., the number of agents that need to make new steering decisions. The average inconvenience per frame $\bar{I}$ is calculated as:

$$\bar{I} = \frac{I}{T}. \quad (7.9)$$

7.2.4 Simulation Results

7.2.4.1 Generation of Crowd Phenomena

Two different corridor scenarios as shown in Figure 7.48 are used to qualitatively test the three models. In the first scenario (Figure 7.48(a)), a narrow corridor with a bottleneck area is used to test a massive crowd with unidirectional flow. In the second scenario (Figure 7.48(b)), a narrow corridor is used to test a group of pedestrians with bidirectional flow.

Different crowd phenomena are literally reported in these corridor scenarios. As described by Still [201], the “edge effects” occurs in narrowed corridors, where people near the wall or the edge of different crowd moves faster. The “wake effect” also occurs in such a corridor, but with a bottleneck formation. When people go through the corridor, right after the end of the bottleneck the crowd maintains itself constricted as if the constricting formation was still there. “Lane formation” is another important crowd phenomenon, where pedestrians self-organize into lanes to avoid interactions with oncoming pedestrians [69]. This helps them move faster than is otherwise possible. Virtual lanes are formed effortlessly and requires no explicit communication [134, 184]. “Swirling”, as described in [59], is a crowd phenomenon where vortices can be observed in crowd flow. In addition, “uneven crowd density” can be often observed in a crowd flow as well [59, 184].

In the first corridor scenario (Figure 7.48(a)), agents are initialized at the left side of the corridor with a Gaussian random preferred velocity ($\mu=1.33$ m/s, $\sigma=0.3$ m/s) to exit the corridor from the right side. We use different colors to indicate the speed

Figure 7.51: Simulation results of a crowd with unidirectional flow in a corridor with a bottleneck.

of the crowd. Agents with higher speed are shown in darker color. The simulation results of the three simulation models are shown in Figure 7.51.

In this scenario, the movement and distribution of agents can be investigated in three difference phases according to their spatial occupation in the corridor. In the first phase, agents move from the left side of the corridor into the bottleneck area. (The slope at the two sides of the bottleneck is designed to prevent severe congestion at the two sides of the bottleneck as suggested in [69, 93]) The uneven density distribution of the crowd can be observed from the PBS model (Figure 7.51(a)), where the two corners along the slope at the bottleneck is more dense than the middle. Consequently, the speed of the agents at the sides are slower (as shown in lighter color) than those in the middle. Such a simulation result is consistent with the literature [176, 201]. It is also observed that agents in the middle of the corridor right before the bottleneck remain similar (but slightly slower) speed as their average speed in the whole corridor (see the light grey colored agents at the middle of the bottleneck entrance in Figure 7.51(a)). Such results naturally reflect the crowd's movement at the bottleneck in the scenario. The emerging behaviors of the agents also generate a relatively high crowd throughput in such a situation. In this scenario, the agents behind are most likely to adopt the *follow* steering strategy, which implicitly regulates the crowd flow so that the agents can move in a relatively consistent speed through the bottleneck. Such behaviors simply reflect the collective intelligence of crowd [134]. The simulation

results of the other two models are different. In the RVO2 model, all the agents gather before the bottleneck with similar density, they all reduce the speeds more significantly (see the light colored agents Figure 7.51(c)). When individual agents push through the bottleneck, different groups with obvious space between them are formed due to the speed differences formed at the bottleneck. As a result, the throughput of the whole crowd may be affected. In the SF model, all agents gather at the bottleneck with similar distribution as in the RVO2 model. However, the speed of the agents at the bottleneck are generally higher than their average speed across the corridor (see the dark grey colored agents in Figure 7.51(e)). Such an increase of speed at the bottleneck is due to the closer distance of agents, and thus the larger repulsive forces generated among each. However, this may seem unnatural as pedestrians' speeds are likely correlated with the density in the reverse order as reflected by the fundamental diagram [185]. It is also observed that the space between each agent in the SF model is generally larger than the previous two models due to the virtual forces.

In the second phase, agents move within the narrow corridor after the bottleneck. The edge effect of the crowd is obvious in the PBS model, compared to the other two models (Figure 7.51(a), 7.51(c) and 7.51(e)). Swirling is also detected in the crowd of the PBS model. Small vortices are shown within the crowd, which is different from the RVO2 model and the SF model, where the crowd are automatically separated into different groups (RVO2), or the crowd seems to evenly distribute along the corridor without obvious vortices among them (SF).

In the last phase, agents leave the narrower area and move into the normal corridor again. The wake effect can be observed from the trails of agents of all the three models (Figure 7.51(b), 7.51(d) and 7.51(f)), though subtle difference in agents' trail after crossing the bottleneck area can be observed. Agents spread out to occupy the whole corridor again fastest in the SF model, and latest in the RVO2 model. In general, the trails of agents are smoother in the PBS and RVO2 than the SF model. Through the simulation in this scenario, most of the previously reported crowd phenomena can be generated in the PBS model, compared with the other two models.

In another corridor scenario as shown in Figure 7.48(b), two groups of agents approach from opposite sides of the corridor. A well recognized crowd phenomenon, lane-formation is commonly reported in this scenario. Virtual lanes are said to form spontaneously in the crowd as the counter flows pass through each other. A more detailed study on the phenomenon has been reported most recently in [147], which suggested that a more realistic lane-formation behaviors can be assessed quantitatively

based on various density, velocity, and the overall status transition of the crowd. Their work has suggested several qualitative measurement of the phenomenon, which they consider to be realistic, and can be applied in our qualitative analysis of the simulation results. For example, they observed that a longer lifetime of the formed lanes would help the pedestrians to reduce chance of jam and disordered flow. They also suggested that the lane formation should happen earlier as a consequence of pedestrians' anticipation to avoid the jam when the counterflow confront in the middle of the corridor. Further, two to three lanes are normally formed in a narrow corridor. Lastly, asymmetric lanes are more realistic than symmetric lanes formed in the crowd.

Figure 7.52: Simulation results of three models in the corridor scenario.

The simulation results of the three models in this test scenario are shown in Figure 7.52. In the PBS model, agents with the same moving direction form into lanes automatically early before they get close with agents of different moving directions. The lanes remain until the two group of crowd cross each other. Two or three lanes are formed in the corridor as a result of interaction among individual agents through applying either the *side-avoid* or *follow* steering strategy. Since different agents may adopt the *follow* steering strategy at different time, asymmetric lanes can be formed naturally with different number of agents in the lanes. Such results are consistent with the observations on the realistic lane-formation phenomenon as reported in [147]. Lanes can also be observed from the simulated crowds of the other two models. However, there are several differences compared with the results of the PBS model. First, the lanes are formed much later in the RVO2 and SF model as a result of the interaction among agents. Since agents' motion are determined on pair-wise calculation of their velocities with each agent nearby, the lanes seem to break and reform at arbitrary time, thus to make the lanes unstable with shorter life-time. Lastly, more lanes with less agents within each, are likely formed in these models as shown in Figure 7.52(b) and 7.52(c).

In this section, the three models are compared qualitatively through the simulation results in two corridor scenarios. We can say that facial validity of the PBS

model has been achieved by successfully replicating various previously reported crowd phenomena realistically.

7.2.4.2 Quantitative Measure

To further assess the simulation results of the three models quantitatively, the metrics previously discussed are measured in different scenarios. Since random variables are used in all the three models, we replicate simulation of a same configuration for 100 times to account for the variation in the results.

Corridor Scenario

The corridor scenario (Figure 7.48(b)) with two groups of agents coming from both sides is tested. Metrics are measured for the three models and are summarized in Table 7.6. The baseline value for each metrics are calculated based on the constant average speed of agents, assuming there is no interaction among any pair of agents.

The best score (in terms of the closest result to the baseline value) in each metric of the three models is highlighted in bold. It is noted that the PBS model outperforms the other two models in terms of simulation time T , total traveling distance L , total biomechanical energy consumed E , total biomechanical energy used in steering E_s , and the cognitive effort measured in terms of the inconvenience I , and average inconvenience per frame $\bar{I}$. However, RVO2 achieves the best scores in metrics that directly reflect the locomotion of agents, i.e., the total change of speed $\sum \Delta|V|$, and direction $\sum \Delta|A|$, and the average acceleration a and angular change α . We discuss in detail for each metric measured in the following section.

The distributions of total distance traveled are shown in Figure 7.53. According to the relative positions of the two groups of agents in the corridor scenario, we can briefly divide the whole interaction into three phases T_1 , T_2 and T_3 as shown in the figure. During T_1 , agents from both sides of the corridor start to move, but they are still far from the other group. In this period, the value of L produced by the PBS model starts to increase from around frame 100, while the other two models produce relatively constant value of L . This indicates that agents start to steer and avoid the oncoming group earlier in PBS than the other models. During T_2 , agents from the two groups encounter each other in the middle of the corridor and avoid collisions with each other. A significant drop in L (i.e., also reflecting the overall speed of agents) is observed in the RVO2 and SF models, while L remains relatively constant in PBS. The overall speed of agents is not reduced too much in the PBS model even in the dense scenario when the two groups get close. Such a result can be attributed to the

Table 7.6: Summary of aggregated metric measure of models in the *corridor* scenario.

Metrics	PBS	RVO2	SF	Baseline
T (frm)	673.03 (24.16)	790.94 (122.67)	731.03 (47.43)	511.28
L (m)	1056.88	1056.96	1107.69	1040
D(m)	50.2	25.65	80.96	0
$\sum \Delta V $ (m/s)	390.2	79.7	596.5	0
a (m/s ²)	0.36	0.063	0.51	0
$\sum \Delta A $ (°)	20388	2674.7	127782	0
α (°/s ²)	18.93	2.12	109.25	0
E (kJ)	254.31	255.82	266.75	253.38
E_s (kJ)	133.41	135.63	163.14	0
I (agts)	1300.1	4777	6519.2	0
$\bar{I}$ (agts/frm)	1.93	6.04	8.9	0

early adoption of steering strategies in the PBS model in T_1 . By following others in the front, agents do not need to reduce their speeds significantly to resolve collisions with the oncoming agents. Such simulation results reflect the natural intelligence of pedestrians' steering behaviors in daily life, where they maintain a smooth motion with relative constant speed even in dense situations. Consequently, the overall time to complete the simulation is shorter in PBS than the other two models (see T_3).

Figure 7.53: Total travelled distance (L) in the corridor scenario.

Figure 7.54: Total deviation distance (D) in the corridor scenario. Figure 7.55: Total direction change ($\Delta|A|$) in the corridor scenario.

The steering behaviors of the agents can be investigated through the vertical deviation distance (Figure 7.54), the total direction change (Figure 7.55) and the total speed change (Figure 7.56) of agents. It is observed that the curves of the three metrics are similar, because they are all attributed to the interactions among agents, but are presented from different perspectives. RVO2 produces the minimum values in the three metrics, followed by the PBS model. SF model generates more deviation, and changes in direction and speed due to the frequent oscillation of agents as a result of the virtual forces. It is also observed that SF produces a much stiffer increase in the metrics within a shorter period of time than the other models as a consequence of

Figure 7.56: Total speed change ($\Delta|V|$) in the corridor scenario.

the effective range of forces, while the effective range can be extended further in both the RVO2 (through the time horizon parameter) and PBS (through the multi-layered attention range).

Figure 7.57: Total biomechanical energy incurred (E) in the corridor scenario.

To investigate the overall dynamics of the crowd in the scenario, we measure the biomechanical energy spent by all the agents in the whole process, and during steering behaviors as shown in Figure 7.57 and 7.58 respectively. PBS generates the minimal energy and steering energy in the scenario, which are slightly less than RVO2. Energy spent by agents in SF is much larger than the other two models. It is also observed

Figure 7.58: Total biomechanical energy incurred through steering (E_s) in the corridor scenario.

Figure 7.59: Total inconvenience incurred (I) in the corridor scenario.

that the energy generated by agents are more consistent (which reflects that the speed of agents are more consistent) in PBS and RVO2 than SF, which generates a pulse increase in steering energy when the two groups of agent encounter at around frame 250 (Figure 7.58).

The cognitive effort made by agents to determine new velocities in order to avoid collisions is measured through the *inconvenience* as shown in Figure 7.59. The changing pattern of the inconvenience value of the three models are similar. The inconvenience slightly increases first until the two groups of agent get close. Then it increases

more significantly when all the agents are getting closer to each other. After the two groups cross each other, the value decreases again. PBS generates the minimal inconvenience value. This is because the agents in PBS do not make new decisions on choosing their velocity until either they have finished the current selected steering strategy or the current situation has violated their current steering strategy. The proactive application of steering strategies helps them plan their route and motion properly, thus minimizing the cognitive effort of making new decisions. For the RVO2 model, the motion of an agent is determined based on the comparison of velocities with every other neighboring agent for the period of time as specified by the time horizon parameter, thus it is likely that the decision made by the agent results in potential collisions after the short period of time specified by the time horizon. As a result, it generates larger inconvenience value than the PBS model. Similarly, agents have to make new decisions as the consequence of several affecting virtual forces in a near range in the SF model. Thus when agents get close to each other, a large amount of inconvenience is required for all the agents to resolve collisions with each other.

An interesting observation from the results above is that RVO2 performs the best in all these metrics that are directly related to the locomotion of the agents. However, for the aggregated metrics such as L , E , E_s and I , RVO2 does not outperform PBS. Such results raises a fundamental issue that the formulated optimized solution in motion control for every agent does not necessarily result in the best solution (measured by the metrics as discussed in this thesis) for the whole crowd. PBS, on the other hand, produces the results that seem to reflect the collective intelligence of pedestrians. The steering behaviors of pedestrians seem to be replicated more realistically through the selection and execution of various steering strategies as discussed in the previous chapters.

Cross Scenario

We have conducted the experiments for the three models in the cross scenario (Figure 7.49). The simulation results at key frames for the three models are shown in Figure 7.60. In PBS, agents in the same moving direction form into groups (lanes) to avoid collisions with the other group of agents coming orthogonally (Figure 7.2.4.2, 7.2.4.2). This is achieved through the application of the *follow* steering strategy made by the agents at the behind of a group. In RVO2, agents generally deviate less, but likely move in a “stop-and-move” manner to avoid collisions with the agents from the other group. Consequently, when crossing the center of the corridor, agents are more separated (Figure 7.2.4.2). In SF, agents react to each other when they are in close

Table 7.7: Summary of aggregated metric measure of three models in the *cross* scenario.

Metrics	PBS	RVO2	SF	Baseline
T (frm)	635.57 (58.13)	636.35 (95.87)	774.65 (186.35)	368.42
L (m)	789.41	764.77	819.65	736
$D(m)$	102.7	55.16	111.43	0
$\sum \Delta V $ (m/s)	805.76	69.1	780.7	0
a (m/s^2)	0.79	0.068	0.63	0
$\sum \Delta A $ ($^\circ$)	73966.4	3653	219456	0
α ($^\circ/s^2$)	72.7	3.59	177.06	0
E (KJ)	193.21	184.87	201.12	184.0
E_s (KJ)	113.09	98.85	138.78	0
I (agts)	2474.32	4236.15	6748.83	0
$\bar{I}$ (agts/frm)	3.9	6.66	8.71	0

distance (Figure 7.2.4.2). Due to the effect of repulsive forces, agents separate from each other similar to how they behave in RVO2. However, it is observed that agents may enter a deadlock situation where the forces between them almost counter-affect each other (Figure 7.2.4.2). As a result, it takes much longer for the two agents to cross each other and to finish a simulation run (capped at 1000 frames).

The summary of the metric measure in this scenario for the three models is shown in Table 7.7. PBS achieves the closest score in the completion time T and the inconvenience I and $\bar{I}$ compared with the baseline values, while RVO2 is the closest in all the other metrics. Each metric measure of the three models is shown and discussed as follows.

Figure 7.61 shows the distributions of the traveling distances L . Similar to the corridor scenario, three different phases can be observed. In the first phase T_1 , agents in the PBS model move slower than they are in the RVO2 and SF models. This is due to the early application of the *follow* steering strategy for agents at the rear of a group. While agents' speed (thus the traveling distance) reduces in RVO2 and SF when the two groups of agent get close to interact with each other in T_2 , agents in PBS remain consistent due to their early application of steering strategies as discussed in the corridor scenario. During T_3 , the two groups of agents cross each other. Since agents form into group in the PBS model, the density at the intersection corner of the

Figure 7.60: Simulation results of three models in the cross scenario.

two corridors is relatively higher than the other two models. As a result, the speed of agents decrease faster (from frame 200 to 300). However, after they pass the corner, some agents adopt the *overtake* steering strategy to move faster. Therefore, the value of total traveling distance L is slightly larger in PBS.

The total deviation distance D of agents is shown in Figure 7.62. The total change in direction and speed are shown in Figure 7.63 and 7.64 respectively. It is observed that RVO2 still achieves the minimal value as it performs in the corridor scenario. PBS performs on par with SF in this scenario, while it performs much better in the corridor scenario. This could be due to the smaller percentage of time that steering strategies are applied by agents to plan their motion in this scenario. The vision of the agents is tightly constrained by the corridor in the cross scenario. They only react to the other group coming orthogonally at the center of the corridor when they can sense each other. Consequently, more agents resort to instinctive reactions to avoid collisions, while others behind still follow the ones in the front.

Although PBS does not generate the minimal values in these metrics on the locomotion of agents, we argue that such a result could indicate more realistic human behaviors, compared with the artificially optimal solutions provided by the RVO2 model. In real life situations, pedestrian may perceive different spatio-temporal patterns in different situations. In some situations (e.g., corridor), it is easier for them to identify such patterns that lead to a certain steering strategy, while in others, patterns are much less obvious (like the cross scenario discussed here) due to the complexity of the spatial constraints. It is also worth mentioning that by extending the current steering strategy pool and corresponding prototypical spatio-temporal patterns, the PBS model can achieve better results in such situations. However, an issue arises here as to whether the introduction of such complex patterns and less obvious steering strategy is necessary (subject to more empirical evidence showing that people do apply certain complex steering strategies in such cases).

The collective efficiency of agents are measured by the biomechanical energy they spent in total and in the steering behaviors as shown in Figure 7.65 and 7.66 respectively, and the cognitive effort they spent during the process which is measured by the inconvenience metric as shown in Figure 7.67. The PBS model performs on par with the RVO2 model, which are much better than the SF model measured by the biomechanical energy. PBS model still outperforms the other two models in terms of inconvenience, but with less advantage compared with the RVO2 model as was for the corridor scenario. This reasonably reflects the fact that a smaller percentage of

Figure 7.61: Total travelled distance (L) in the cross scenario. Figure 7.62: Total deviation distance (D) in the cross scenario.

time and agents are adopting steering strategies continuously in this scenario due to the spatial constraints.

In summary, RVO2 achieves the closest score to the baseline values in metrics that are directly related to the locomotion of agents in the cross scenario. PBS, on the other hand, performs slightly better than the other models in aggregated metrics to reflect the collective efficiency of the crowd both biomechanically and cognitively. SF, due to the oscillation caused by the repulsive forces, generates the worst result in these metric measure. Compared with the previous corridor scenario, RVO2 and SF generally produce similar scores in this scenario because of their single motion

Figure 7.63: Total direction change ($\Delta|A|$) in the cross scenario. Figure 7.64: Total speed change ($\Delta|V|$) in the cross scenario.

control mechanism regardless of the situation. However, PBS sees a difference in performance across these different situations, which naturally reflects the variance of collective behaviors presented by pedestrians in real life situations.

Circle

The simulation results of the three models are demonstrated in Figure 7.68. It is noted that a symmetric formation of agents was initialized in such a situation. In PBS, agents start to deviate early by applying the *side-avoid* steering strategy (as indicated by the outer dotted circle line in Figure 7.2.4.2). Due to the asynchronous execution of such a steering strategy, there is no deadlock situation in resolving collision. When

Figure 7.65: Total biomechanical energy incurred (E) in the cross scenario.

Figure 7.66: Total biomechanical energy incurred through steering (E_s) in the cross scenario.

agents get close to each other in the center (see the inner dotted circle line in Figure 7.2.4.2), they mainly resort to instinctive reactions (based on RVO2) for collision avoidance as no proper steering strategy is selected. In RVO2, there are two types of simulation results observed from the 100 replications. In the first type, agents enter a deadlock situation (Figure 7.2.4.2), where the available velocity for an agent to avoid collision while moving towards its goal is gradually eliminated as they move into a small circle. Since the calculation of velocity for each agent is based on a single optimal solution, each agent is expecting the others to contribute half of the effort in

Figure 7.67: Total inconvenience incurred (I) in the cross scenario.

resolving the deadlock. They react in a very similar way to each other. Eventually, they end up in a deadlock situation. A small perturbation parameter can also not resolve the deadlock in such a situation because of the high density at the interaction area as denoted by the dotted circle line in the figure. In other simulation results, agents break the symmetric situation around the dotted circle line as shown in Figure 7.2.4.2, and thus resolve the collision and deadlock properly. This is probably due to the speed variance of agents as initialized in such a test case. Since agents only react to each other within a certain distance as specified by the time horizon parameter in the RVO2 model, the position variances of agents are subject to their traveling distances (i.e., around 8 m before reaching the interaction area) and the speed variance (i.e., 0.3 m/s to mimic normal moving speed of pedestrians). In SF, agents start to react to each other at a short distance as denoted by the dotted circle line shown in Figure 7.2.4.2. Due to the repulsive forces, it takes much more time than the PBS model to resolve the deadlock situation. It is further observed that agents in the SF model always start to rotate and resolve the deadlock from the most external layer of the crowd.

The summary of the metric measure for the circle scenario is shown in Table 7.8. It is similar to the corridor scenarios, PBS achieves the closest score in aggregated metrics such as T , E , E_s , I and $\bar{I}$, but RVO2 is the closest in the locomotion related metrics. However, it is noted that RVO2 models do not always finish the simulation within the predefined simulation time of 1000 frames. SF generates the largest difference in these metrics compared with the baseline values.

(a) PBS

(b) SF

(c) RVO2 - deadlock

(d) RVO2 - resolved

Figure 7.68: Simulation results of three models in the circle scenario.

Table 7.8: Summary of aggregated metric measure of models in the *circle* scenario.

Metrics	PBS	RVO2*	SF	Baseline
T (frm)	423.67 (105.26)	827.93 (289.86)	633.81 (156.75)	300.75
L (m)	834.31	344.85	1592.93	640
D(m)	212.43	25.86	561.35	0
$\sum \Delta V $ (m/s)	980.64	79.76	1615.06	0
a (m/s ²)	1.45	0.06	1.59	0
$\sum \Delta A $ (°)	115078.8	4988.36	219456	0
α (°/s ²)	169.76	3.76	216.41	0
E (KJ)	263.01	290.81	454.71	150.19
E_s (KJ)	180.08	250.72	645.05	0
I (agts)	3832.04	19544.24	13250.05	0
$\bar{I}$ (agts/frm)	9.04	26.61	20.91	0

*: RVO2 does not always complete a simulation run within 1000 simulation steps.

Similar to the previous scenarios, individual metrics are measured and discussed in this subsection. The total traveling distance of agents is shown in Figure 7.69. The overall movement of agents can be divided into two phases: the first phase T_1 , when agents move towards the goal without interactions with others; and the second T_2 , when agents interact with each other. All the three models perform similarly during T_1 . It is shown that the value of L drops most significantly once entering T_2 in RVO2 and it drops to zero fast due to the deadlock situation as discussed previously. As agents interact with each other in a relatively short distance, the density becomes higher and the speed gradually drops as a result. Such an observation can also be made from the simulation results of the PBS and SF models. A difference in these two models is that more obvious oscillation is observed in SF. In addition, agents likely complete a simulation run earlier in PBS than the other two models.

The total deviation distance is shown in Figure 7.70. RVO2 generates the least deviation. Since RVO2 does not complete this scenario within the specific simulation time, the discussion on the rest of the metrics will be focusing on the other two models. Comparing the total change of speed and direction made by agents as shown in Figure 7.72 and 7.71, it is observed that PBS generates less speed and directional change than SF. The curve of PBS increases and decreases earlier to reflect such changes. This indicates that agents in the PBS model start to steer early by adopting

the side-avoid steering strategy, and they complete the simulation earlier than those in the SF models.

The biomechanical effort measured by the total energy and the energy spent in the steering behavior is shown in Figure 7.73 and 7.74 respectively. Two key observations can be drawn from these figures. First, PBS generates relatively stable and smaller energy value during the interaction among agents, while obvious drop and rise of the energy is observed in the SF model (see simulation step 100 to 350 in the figures). As the energy is positively correlated with the speeds of agents, it indicates that the speeds of agents are more consistent in the PBS model. The SF model on the other hand, generates much more speed increase due to the repetitive and continuous effect of forces. Secondly, the energy spent in the overall motion of the SF model is subject to the long-tail effect as the model takes a much longer time to finish a simulation run than the PBS model. From such metrics, it indicates that steering strategies are effective to help pedestrians resolve collisions in even relatively dense situations.

The cognitive effort made by all the agents are measured by the inconvenience metric, and is shown in Figure 7.75. PBS achieves a much lower value than the other two models. Such a finding is consistent for all the three test scenarios, and is the same as previous scenarios.

Figure 7.69: Total travelled distance (L) in the circle scenario.

In this scenario, RVO2 likely fails to complete the simulation run within the maximum simulation time because of the deadlock situation. SF generally completes a simulation run with longer time than PBS, due to the conflicting forces produced in the dense crowd at a close distance. Such simulation results may indicate that the

 Figure 7.70: Total deviation distance (D) in the circle scenario.

 Figure 7.71: Total direction change ($\Delta|A|$) in the circle scenario.

PBS model is more capable of replicating the collective efficiency of a simulated crowd in such a scenario.

7.2.5 Discussion

In this section, we have first reviewed the existing test scenarios used in the previous work, and have categorized them based on the number of main motion axes (mma) involved in the scenarios. According to different number of mmas, we adopt three typical existing scenarios and designed the experiments to test and compare the performance of three models. The models are compared both qualitatively and

Figure 7.72: Total speed change ($\Delta|V|$) in the circle scenario.

Figure 7.73: Total biomechanical energy incurred (E) in the circle scenario.

quantitatively so as to validate the PBS model.

Through the simulation studies of a massive crowd with both unidirectional and bidirectional flow in two corridor scenarios, various crowd phenomena are tested and evaluated. Such phenomena are commonly used as the criteria to evaluate the simulation result of a model qualitatively. The simulation results of the PBS model are in good agreement with literature studies that describe these crowd phenomena. Facial validity of the PBS model is certainly achieved through successfully replicating these crowd phenomena realistically.

The quantitative analysis of various metrics on crowd dynamics is then carried out

Figure 7.74: Total biomechanical energy incurred through steering (E_s) in the circle scenario.

Figure 7.75: Total inconvenience incurred (I) in the circle scenario.

to add confidence further to the validity of the PBS model. Such metrics are taken from the existing work to measure the crowd dynamics from various aspects (i.e., both locomotive and collective efficiency). Through the comparison of metric measures on the three models across three scenarios, several observations can be made:

- Collective efficiency of the crowd (e.g., measured by both the physical and cognitive effort) is not necessarily achieved through optimal calculation on the locomotion of each individual in the crowd. A crowd is a complex system, and each individual contributes to the overall order of the system. For individuals,

it is not necessary an optimal choice in its movement (e.g., pedestrians detour to avoid congestion), but their movements contribute to the overall efficiency of the crowd. PBS models the movement of pedestrians as a consequence of the cognitive process. Through the pattern-matching and steering strategy execution, minimal effort emerges from the interaction of the crowd and natural behaviors of them are achieved.

- Models such as RVO2 and SF achieves relatively consistent performance across different scenarios, while PBS sees the variances in its performance. In general, it is expected that the performance drops as the number of mmas increases. From the perspective of the PBS model, such variances can be mainly attributed to the limited experience of agents in perceiving and matching corresponding STPs in different situations. As the situation becomes more complex, it is more difficult to identify corresponding STPs from the situations. Alternatively, it is likely that hardly any patterns can be perceived from a complex situation in the first place. In such cases, pedestrians probably resort to instinctive reactions in order to avoid collisions in a crowd. We argue that this reflects pedestrians' perception capability and different behaviors in different situations realistically.

Through both the qualitative and quantitative analysis of the simulation results, the validity of the PBS model has been demonstrated.

7.3 Sensitivity Analysis

7.3.1 Motivation

In the previous sections, the PBS model is validated against other models in various scenarios based on a set of specified initial conditions and pre-calibrated parameter values (e.g., personal space factor, commitment level of an agent etc.). These parameters are adopted from existing pedestrian studies or designed to estimate their effects on pedestrians' motion behaviors realistically and they are assigned as either static values (e.g., personal space factor) or random values (e.g., commitment of an agent). For a complex behavioral model, parameters represent quantities that are very difficult, or even impossible to measure to a great deal of accuracy in the real world [87]. Also, some parameter values change in the real world dynamically. In such a case, sensitivity analysis can help understand the impact, which a particular parameter has on the result. This can in turn help guide the modelers in the measurement of real

world data in order to tune the parameters. That is to allow the modelers to focus on establishing accurate values for the parameters which have the largest impact. To further add confidence to the PBS model by studying the uncertainties and different significance associated with different parameters in the model, sensitivity analysis is conducted and discussed in this section.

Sensitivity analysis is used to determine how “sensitive” a model is to changes in the value of the parameters of the model and to changes in the structure of the model [179]. In this thesis, we focus on parameter sensitivity to evaluate the proposed PBS model with a fixed structure. Parameter sensitivity is usually performed as a series of tests that to set different parameter values and to see how a change in the parameter causes a change in the dynamic behavior of the model. By showing how the model behavior responds to changes in parameter values, sensitivity analysis is a useful tool in both model development and evaluation. Particularly for model evaluation and validation purposes, sensitivity analysis can be useful in various aspects [153] including testing the robustness of the results of a model in the presence of uncertainty; increasing understanding of the relationships between input and output variables in a model; identifying model inputs that cause significant uncertainty in the output; and finding input space that leads to desired outputs.

One of the most common approaches in sensitivity analysis is that of changing one-factor-at-a-time (OFAT or OAT), and to see what effect this produces on the output [138]. OAT customarily involves changing one model parameter, keeping others at their baseline (default) values; and then returning the parameter to its baseline value, repeating for each of the other parameters in the same way. Sensitivity is then measured through the changes in the output. We apply this approach in conducting sensitivity analysis for the PBS model.

7.3.2 Experiments and Results

Three parameters are selected for sensitivity analysis because they are expected to have most influence on the model’s behavior and we want to quantify the significance of such parameters to the simulation results. The parameters are x_1 : the *variance in preferred speeds* of the agents; x_2 : the *personal space factor* of the agents and x_3 : the *commitment level* of all agents. All the tests are conducted in the corridor scenario used in the previous section (Figure 7.48(b)). We measure the change of model’s behavior through both qualitative observation on the simulation results and the quantitative metrics as discussed in the previous stage of validation. The parameter values vary in the range as summarized in Table 7.9. Such value ranges are

Table 7.9: Variables and their value ranges for sensitivity analysis.

Variable	Value Type	Value Range	Baseline value
preferred speed sd (x_1)	float	[0 m/s, 2.0 m/s]	0.3 m/s
personal space factor (x_2)	float	[0, 2.0]	0.3
commitment level (x_3)	float	[0, 1.0]	0.5

selected to represent the plausible range that could theoretically occur in the real world system (including some extreme conditions).

For each parameter setting, we replicate 100 simulations and obtain the average value for the metric measures. We then normalize the metric values along different parameter settings (against the average of the metric values for all the parameter settings) to obtain the *normalized metric values* and plot the results as shown in Figure 7.76. The results indicate that the model is more sensitive to initial preferred speeds of agents with a standard deviation less than 0.6 m/s. As the speed variance further increases, the model is not sensitive to any change, as shown in Figure 7.76(a). The result indicates that as the speed variances increase (from 0 m/s to 0.6 m/s), more effort is made by agents to finish the simulation. This is consistent with the observations that speed variances of individuals contribute to the “chaotic” crowd dynamics made in previous pedestrian studies [70, 201]. This experimental result also reveals that further speed variances may not affect the overall crowd dynamics significantly. This could be due to the fact that the actual moving speed of agents are constrained through applying steering strategies at the early stage of simulation.

From the results of different personal space factor values as shown in Figure 7.76(b), we observe a significant impact on the overall crowd dynamics. The personal space factor is virtually perceived as the extra space surrounding the body of an agent to imitate the social space pedestrians reserve among each other in a crowd. The value of this parameter affects the number of columns in the formed concrete STP, and it essentially reflects the perceived density of the local space. That is, a larger personal space factor value indicates a higher local density perceived by the agent. As density increases, the slower the agents are the more effort is required to complete the session over a longer period of time. Such results are consistent with the fundamental diagram [185], which indicates the reverse correlation of density and speed of a crowd.

The results of different commitment levels are shown in Figure 7.76(c). Commitment level is designed to represent different experience levels of individual agents on selecting a steering strategy upon partial match of the STPs. If a steering strategy

(a) standard devaiitin of preferred speed

(b) personal space

(c) commitment level

Figure 7.76: Sensitivity tests of the PBS model.

is selected due to a high degree of match, it is more likely that it will not be violated during the execution process, which should lead to more efficient crowd dynamics. However, the results are counter-intuitive in this sense. As the commitment level increases, measured metrics also increase (less crowd efficiency). In this case we hypothesize that the density impacts the influence of the commitment level. In less dense scenarios, agents with a higher commitment level may choose steering choices with more constraints matched, thus more fluent steering behaviors are expected. However, the high density may constrain the agent's choices. With a higher commitment level, the chance for agents to overtake is even lower. From this study, it may indicate more impact of the external factors (density) than the internal (commitment) in the PBS model.

Through the sensitivity analysis on the key parameters of the PBS model, it indicates that the model is generally robust to changes in key parameters. That is the generated crowd behaviors change with the parameter values in a manner that is consistent with the literatures. Besides, such an analysis also raises a fundamental research issue in a complex system: the simulation results may be influenced by various model parameters in a non-linear manner. Through the sensitivity analysis, modelers can identify more significant parameters. In this model, the external factors such as the perceived density have more influence on the steering choices of the agents, compared with internal factors such as the commitment level.

7.4 Summary

In this chapter, we have adopted the proposed three-stage validation method trying to validate the PBS model. First, we used a set of basic scenarios to test the simple steering strategies proposed in the model and to validate the model thoroughly through comparing the results qualitatively and quantitatively with both field-experimental data and simulation results of other models. At the second stage, we adopted simulation scenarios from existing work that involve more complex crowd interactions to test the PBS model against other models. Various metrics were used to quantitatively measure the simulation results. At the last stage, we conducted sensitivity analysis on the PBS model to demonstrate its robustness and to identify the impact of different key parameters to the simulation results. The validation process, with its objectives and key findings, is summarized in Table 7.10.

Through this validation process, the facial, functional and quantitative validity of the PBS model is achieved. Such a validation method follows a typical scientific

approach; and it is one of the few works, so far as the author is aware, that has attempted to validate a steering behavioral model in such a systematic and comprehensive manner.

Table 7.10: Summary of key findings from each validation process.

Validation Stage	Methods	Objectives	Key Findings
One (Section 7.1)	Field experiments (selected scenarios)	<ul style="list-style-type: none"> To study various motion features of participants during their interaction. 	<ul style="list-style-type: none"> Visually perceived constraints of a situation affect a participant's steering choices. Participants tend to perceive others with similar motion features as a group and interact with the group. Individuals or participants in a small group tend to avoid larger groups proactively. Participants are capable of measuring the environment well and adapting their motions to achieve specific goals effectively.
	Simulation studies (selected scenarios)	<ul style="list-style-type: none"> To validate the PBS model thoroughly through comparing results qualitatively and quantitatively with both experimental data and two other models 	<ul style="list-style-type: none"> The PBS model generates much closer simulation results to the experimental data than the other two models in all three scenarios.
Two (Section 7.2)	Simulation studies (Standard test cases under more complex scenarios)	<ul style="list-style-type: none"> To show that the PBS model can be used to simulate collective pedestrian dynamics under different complex scenarios. To demonstrate that the PBS model can perform comparatively well in various complex scenarios, and thus to demonstrate the robustness of the pattern-based approach. 	<ul style="list-style-type: none"> Facial validity of the PBS model is achieved by producing various crowd phenomena reported in the previous literature. The collective efficiency of the simulated crowd is better achieved in the PBS model than the other models. The natural variances of various motion features and collective dynamics under different contexts (scenarios) are produced by the PBS model rather than the other models.
	Sensitivity Analysis	<ul style="list-style-type: none"> To demonstrate the robustness of the PBS model and to study the impact of its key parameters. 	<ul style="list-style-type: none"> The simulated crowd behaviors in the PBS model change with the parameter values in a manner that is consistent with the literatures. It suggests that the external factors may have more influence on the steering choices of the agents than the internal ones, from the different impacts of parameters on the simulation results.

Chapter 8

Conclusion and Future Work

This chapter concludes the work described in the thesis, summarizes the key contributions, and points out several research issues that are recommended for the future work.

8.1 Conclusions

It is remarkable to observe that a large number of pedestrians navigate along pavements without bumping into each other. It is therefore interesting to ask whether we could develop advanced algorithms to drive virtual characters in a simulation so that they can move in a human-like way. Simulating human-like pedestrian behavior has many important applications in computer animation, digital entertainment, civil planning, military training, etc. This thesis has made some contributions towards modeling human-like steering behaviors of pedestrians.

To help understand pedestrian behaviors thoroughly, and to direct the research work described in this thesis, existing work was first reviewed mainly from two aspects in Chapter 2. Previous pedestrian studies were reviewed from the social, psychological and ergonomic perspectives, and the review of existing simulation models on pedestrian behaviors was then used to provide an overview of the state of the art from the modeling point of view. Such a review was then applied to form theoretical basis of the approach proposed in the thesis in order to overcome some drawbacks of the existing approaches.

The theoretical basis for the pattern-based approach was elucidated in Chapter 3. Several assumptions to describe and explain pedestrians' navigational behaviors were proposed. Based on these assumptions, a tri-layered modeling structure for motion of pedestrians was then proposed. The cognitive process of perceive-decide-act that

is likely involved in the navigation process of a pedestrian was discussed. Such discussions have identified several design issues for the model to address in simulating pedestrians' behaviors realistically. Firstly, a novel *local path determination* layer, somewhere between the path planning and locomotion, was proposed, where complex steering behaviors of pedestrians are assumed to emerge from a limited number of steering strategies. The proposed model focused on this layer in the behavioral modeling of pedestrians. Secondly, a pattern-based approach was suggested to model the key components of the cognitive process such as the perception, decision and action.

Being a key concept of this thesis, Spatio-Temporal Patterns (STP) were discussed separately in Chapter 4. A pattern description method was then proposed for describing and specifying an STP. The conceptual STP, thus described, can be applied in a model. Chapter 5 then depicted the pattern-based steering model for the strategic steering behavioral modeling of pedestrians. Each of the key components in the perceive-decide-act cognitive process were discussed under the pattern-based approach. Perception is modeled through a three-step situation assessment process, where concrete STPs are formed from the situation, similar to the formation of situation awareness. A hierarchical pattern matching process is then applied to mimic the decision-making process, which utilizes the experience of pedestrians in a way that to adopt different steering strategies according to the matched prototypical patterns. Three steering strategies have been developed, and the execution process of these steering strategies forms the action system of the proposed model. Several potential advantages of the pattern-based approach such as the human-like perception, naturalistic decision making, realistic strategic level steering behaviors, intuitiveness and the extensibility for modelers to use and develop were also discussed in the chapter.

Through the research work on pedestrian behaviors as described in the thesis, it has been shown that agent-based modeling and simulation is an important and useful tool to study human-related behaviors and mechanisms. The idea that relatively simple and recurrent rules can produce rich and complicated behaviors reflects the beauty of a multi-agent system. As demonstrated in this thesis, complex steering behaviors can emerge from the selection, scheduling and execution of a limited number of simple steering strategies. Each steering strategy represents certain sequences of actions, which can be modeled and combined to achieve complex behaviors.

To address the challenges in evaluation of the proposed model, Chapter 6 has separately discussed the difficulties, motivations and feasible approaches in the evaluation (particularly from the validation aspect) of microscopic pedestrian simulation models.

The review of the existing validation methods categorized different validation types of a simulation model along two dimensions, and identified various validation techniques for each validation type. Based on such a review, a three-stage validation methodology for the pattern-based steering model has been proposed. A key contribution of this chapter is that the comprehensive review and the categorization of the ad-hoc validation works of crowd simulation models provides a state-of-art benchmark in the validation of general human-behavioral models.

Using the validation methodology presented, extensive experiments and simulations were conducted, and the results were discussed in Chapter 7. Various techniques such as controlled field experiments, model alignment under standard test cases (i.e. complex crowd scenarios), and sensitivity analysis were applied. A set of basic scenarios were used to test the simple steering strategies proposed in the model and to validate the model through comparison of the experimental data and the simulation results of different models. A set of standard test cases which involve more complex crowd interactions were then applied to test the models. Both qualitative crowd phenomena and quantitative motion features and crowd dynamics have been evaluated to compare different models. Finally, it was demonstrated that the PBS model is robust enough to generate different steering behaviors according to different values of key parameters. In summary, the validation methodology demonstrated facial, functional and quantitative validity of the PBS model.

To apply a complex model in real applications, it is always important to evaluate and validate the model. A general observation drawn from the thesis is that a hard (absolute) validation of a simulation model (especially that relates to human behaviors) is very difficult to achieve. This is because the structure and mechanisms of the original system are simply too complex to be fully understood. In such a case, a systematic validation process is important to provide evidence for different aspects of a model. For instance, different validation techniques can be utilized for certain types of validation. Another reflection on the validation of a simulation model is that meaningful data and metrics are important for model validation. However, they usually propose a great challenge for modelers. First, data is scarce for certain specific applications. Gathering valid data itself requires huge effort, which may likely involve a series of field experiments. Secondly, metrics should be selected to measure different aspects of the results according to the specific objectives and applications of a model. For instance, the number of collisions is commonly used to measure a steering model in traditional motion-control approaches. In this thesis, however, it has not been

used because the primary objective of the research is to model human-like steering behaviors of pedestrians. Humans are naturally non-optimal, and collisions do occur in many situations. Instead, motion features and collective efficiency of the simulated crowd have been measured to demonstrate that the proposed model can replicate such characteristics of a crowd, which in turn reflects realistic aspects of pedestrian behaviors.

The proposed pattern-based approach in this thesis is promising in two respects. First, it has demonstrated that such an approach is capable of generating various human-like crowd behaviors, and reflecting different crowd dynamics realistically. Secondly, the approach is intuitive for modelers to develop a specific model, mimicking the experience of pedestrians in their movement, through pattern-matching and steering strategies.

8.2 Future Work

The pattern-based approach is promising in modeling various steering behaviors of pedestrian as demonstrated through the intuitive pattern description and the systematic results validation process. However, given the complexity of human's perception process, the vast diversities in individuals' behaviors, and the unknown structure of the actual experiences that are involved in the interactions among pedestrians, this work has only explored the *actual* pedestrians' behaviors from one of the many possible perspectives, and some of the model design is based on simplified assumptions. It requires significant effort from multiple research fields to continuously contribute to this research area. From the modeling and simulation perspective, further improvements can be made from the following aspects.

The concept of pattern-based decision-making framework can be further extended to model different levels of decisions involved in the navigation of pedestrians across different scenarios in a hierarchical manner. For instance, different steering strategy pools can be constructed to represent different experience and behavior sets that are commonly adopted by people under different context. Such a scenario refers to certain higher level description of the situation, compared with the spatio-temporal information defined for local path planning in this work. The current model focuses on the steering behaviors modeling, and demonstrates various complex steering behaviors emerged from the scheduling and execution of a limited number of steering strategies. Such behaviors generally represent how pedestrians behave in terms of motion in normal scenarios. In other emergent scenarios, such as the fire evacuation, different

sets of steering strategies may replace the current steering strategy pool (e.g. flee, flock etc). To model such a switch of experience sets, certain higher level of patterns can be defined to capture the main features of the scenarios.

In the perception process of the current PBS model, an agent perceives the current situation and forms an concrete spatio-temporal pattern from the situation in the PBS model. The temporal information of the situation is captured through a prediction function, which in the current model, is based on a *linear dead reckoning* method to deduce the spatial features of each sensed agent purely based on its current status. Such an assumption is effective in some cases, but can be further extended to model the mental prediction of human beings more realistically. For example, prediction of the change of the spatial configuration can take into account of the past motion status of the agents. Through the previous and the current position and velocity of the sensed agents, the system can deduce their possible future motion status with certain probability as a stochastic process. Techniques such as the Markov chain [58] can be applied to address this problem. The heterogeneous choices of individual agents can then be enriched through such a probabilistic design. Once the *previous* states of the sensed agent are taken into the perception formation process, a further improvement to the current model can be employed to update the concrete STP only partially. This partial update may mimic the temporal memory of pedestrians more realistically and achieve better computational efficiency at the meanwhile.

Some of the model parameters are specified and calibrated to suit specific scenarios as static values, but dynamic assignment of such parameter values can be developed to make the model more robust, and suitable for different situations. For example, the personal space factor of an agent can be adjustable subject to its subjectively perceived local density of the crowd in the vicinity.

A proper communication system among agents can be further explored to refine the formed concrete STPs. In real life situations, pedestrians communicate with each other either explicitly (e.g., talking) or implicitly (e.g., subtle body gestures) in a crowd to facilitate the overall efficiency. Different social status and norms as reviewed in Chapter 2 can affect their steering choices as well. Pedestrians can even perceive the tentative intention of other people she is interacting with through certain implicit *signals* exhibited from the subtle change of their motions. Such information captured through either way of communication can help pedestrians further refine the predicted frames in the formed patterns and thus to achieve more realistic interaction.

Nonetheless, it is a big challenge in understanding and designing an appropriate communication system, as the information transferred through such a process involves much more complex interaction and synchronization.

The validation of the model can be further improved, benefited from the fast growing video analytic techniques, and potential future findings from the neuroscience, cognitive science research. The PBS model is quantitatively validated through model alignment (i.e., comparison with other simulation models) currently. Crowd motion data of more complex scenarios is hardly feasible and is also difficult to be extracted automatically through video analysis. As more real applications of crowd simulation become desirable, it is important for a model to be validated against real data in complex situations. It is thus becoming critical to obtain more information about crowd motion from real data. With the help of advanced video analytic techniques, various indicators not only on the microscopic, but also the macroscopic level (e.g., velocity field, density distribution, predominant moving direction), can be automatically extracted from video data effectively and to be applied in model calibration and validation [82, 89, 242]. However, it is important to mention that defining meaningful quantitative metrics to evaluate the realism of a crowd simulation result is still an open problem. Another research stream focusing on the visual perception and cognitive imaging from the neural science and cognitive research may help provide further theoretical support on the structural validity of this pattern-based approach. How different spatial and temporal information is made use of in different tasks can then be studied and modeled to form different patterns under the framework.

Lastly, the pattern-based steering model proposed in this work can be further integrated with other high level path-planning model to study the crowd behaviors of pedestrians in various real-world applications. An example can be a crowd control scenario for military training [81]. Through evolving some of the model parameter values, the model generates certain behaviors for the soldier agents (i.e. the agents simulating the soldiers in a military mission) to achieve optimal crowd control. A fundamental question here is whether the model can be evolved by parameter values only to achieve certain results through evolutionary computation, or the structure of the model needs to be evolved as well. Such studies of a complex system would in turn further validate the PBS model structurally.

Author's Publications

Journals:

- **N. Hu**, S.P. Zhou, Z.K. Wu, et al, "Spatial-Temporal Patterns and Pedestrian Simulation", *Computer Animation and Virtual Worlds*, Wiley, vol.21, no.3-4, pp. 387-399, 2010
- **N. Hu**, M. Lees, S.P. Zhou, et al, "Pattern-based Motion for Crowd Simulation", *Transactions on Edutainment*, Springer, vol.1, no.1-2, pp. 99-110, 2011
- S.P. Ting, S.P. Zhou, **N. Hu**, "Generating Situation Awareness for Time Critical Decision Making", *Transactions on Computational Science XII*, Springer, vol.6670/2011, pp.183-205, 2011

International Conferences:

- **N. Hu**, S.P. Zhou, Z.K. Wu, et al, "Spatial-Temporal Patterns and Pedestrian Simulation", *The 23rd Annual Conference on Computer Animation and Social Agents*, St-Malo, France, 2010
- **N. Hu**, M. Lees, S.P. Zhou, et al, "Pattern-based Motion for Crowd Simulation", *The 24th Annual Conference on Computer Animation and Social Agents*, Chengdu, China, 2011
- S.P. Ting, S.P. Zhou, **N. Hu**, "A Computational Model of Situation Awareness for MOUT Simulations", *International Conference on Cyberworlds*, Singapore, 2011
- P.F. Xing; M. Lees.; **N. Hu** et al, "Validation of Agent-Based Simulation through Human Computation : An Example of Crowd Simulation", *Multi-Agent-Based Simulation XII, Lecture Notes in Computer Science*, Springer Berlin Heidelberg, vol.7124, pp.90-102, 2011

- **N. Hu**, J. Decraene, W. Cai, “Effective crowd control through adaptive evolution of agent-based simulation models”, *In Proceedings of the Winter Simulation Conference*, Berlin, Germany, 2012
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Appendix A

Prototypical STP Specification

In Chapter 4, the Pattern Description Method (PDM) was proposed to allow modelers to specify an STP (prototypical STP in particular). We depict the details in specifying the prototypical STPs corresponding to the three proposed steering strategies used in our current model.

A.1 Prototypical Pattern for *Overtake*

A.1.1 Situation Description

In a situation, where the area in front of a pedestrian is and will be partially blocked by someone moving slower in the same general direction with space beside them, the pedestrian will likely adopt the *overtake* steering strategy. From the description, two spatial constraints with their respective temporal constraints can be identified corresponding to the different phases of the execution process for the overtake steering strategy as shown in Figure A.1(a). First, a blockage is perceived in front of the pedestrian caused by some slower walkers with space available to occupy beside them. Such a spatial constraint should sustain for a period of time, during which the pedestrian perceives that she can reach the space through the catching up phase. Secondly, there is space available for the pedestrian to further pass ahead of the target. Such a spatial constraint is set to exist at the slice after the period of time for the first spatial constraint as specified in the STP.

A.1.2 Prototypical STP specification

Based on the two spatial and temporal constraints as discussed, the proposed prototypical pattern for the overtake steering strategy can be specified as shown in Figure A.1(b).

Figure A.1: Situation and specification of the prototypical STP corresponding to the *overtake* steering strategy.

The specification of this prototypical STP consists of two specified slices to reflect the two spatial and temporal constraints as discussed. The first spatial constraint (SC) SC_1 is specified as sections with values “01” in the left half of the slice at the selected range to represent the central front area in the left half of the vision. The “1” indicates the blockage (target to overtake) and the “0” represents the perceived space beside the target. Such spatial constraints sustain for T_0 time steps from the current time step t_0 , which is an instructive period of time that can be calculated in the run time based on the current velocities of the agent and the target to overtake. Note that in this specified slice, only the left half is specified with values to represent SC_1 or its equivalents. This is due to the symmetric features of the vision of an agent and the matching between two STPs will take the symmetry into account as discussed in Chapter 5. The second spatial constraint SC_2 is specified with value “0” in the specified range in the center of the first row in the slice. SC_2 indicates the available space for the agent to further pass ahead once it has caught up with the target. Such a spatial constraint exists at the subsequent frame t_1 after the period of time T_0 as specified for SC_1 .

Since the execution process of the overtake steering strategy is modeled through the two phases as discussed, the overall STP is specified as two specified slices with the instructed number of frames respectively.

A.2 Prototypical Pattern for *Follow*

A.2.1 Situation Description

In a situation, where there are slow walkers in the front blocking the way, but there is not enough space for overtaking, a pedestrian will likely adopt the *follow* steering strategy as demonstrated in Figure A.2(a). Through the description, we identify two components of the spatial constraints and one temporal constraint of the typical situations. First, there are other pedestrian(s) walking in the same general direction in the front that can have blocked the way of the pedestrian. Secondly, there is not enough space available for the pedestrian to overtake. Such spatial constraints (blockage by slow walkers in the front) are required to sustain for a period of time subject to the commitment level of the pedestrians.

A.2.2 Prototypical STP specification

Based on the two spatial constraints described above, we have specified a prototypical STP to represent such a situation, where the *follow* steering strategy is likely adopted. The prototypical STP is shown in Figure A.2(b).

(a) A typical situation where pedestrians are likely to follow.

(b) Prototypical STP corresponding to the *follow* steering strategy.

Figure A.2: Situation and specification of the prototypical STP corresponding to the *follow* steering strategy.

The first step to specify the spatial constraints is to identify the ranges to be specified in the stack of slices. In this STP, the immediate front in the agent's vision center is identified as a range, where the spatial constraints to be indicated. The range is quantified as a ratio of the total number of columns in the slice. The ratio

is adjustable to accommodate different agent's cognitive perception on the concept of "central". This is because people rarely deviate a large angle to follow someone in his vision peripherals [230]. In the STP shown in Figure A.2(b), the number of sections specified in the range is set as $\lceil 0.6 * n \rceil$, where n is the total column number of the slice and 0.6 is a ratio selected to represent the middle area of the vision range in front of the observing agent. Such a value is set based on the observation that it is rare for a pedestrian to detour more than 60° in order to walk in a smooth trajectory.

The next step is to assign appropriate constant values to the identified range to reflect the spatial constraints. In this case, at least one section is set with value "1", and all other sections within the range with the negated value of "0". The "1" indicates the *blockage* caused by the slow walkers and the negated value of "0" for all other sections within the range reflects that "there is no space available for overtaking".

In the temporal dimension, the specified spatial constraint needs to sustain for a period of time T_0 , during which the agent can verify the perceived spatial constraints, for example, to confirm that the blockage of the section with value "1" is caused by some agent moving slower than this agent.

A.3 Prototypical Pattern for *Side-Avoid*

A.3.1 Situation Description

In a situation, where a pedestrian perceives an individual or a group of other pedestrians walking in the general opposite direction from the front, and there are space beside the individual or group for the pedestrian, the *side-avoid* steering strategy is likely to be adopted as shown in Figure A.3(a). From the description, a spatial constraint with its respective temporal constraint can be identified. A blockage in the central area of vision is perceived as some pedestrians moving in the general opposite direction towards the pedestrian. In addition, the space in this area is necessary for the pedestrian to plan deviation early as a strategic move rather than an instinctive reaction to avoid potential collisions. Such a spatial constraint is set to exist at the current frame rather than a period of time. Such a temporal constraint is set to reflect the assumption that people tend to pay more attention to others walking towards them. Thus, once the spatial constraint as described above is perceived, the *side-avoid* steering strategy is likely to be triggered.

A.3.2 Prototypical STP specification

Based on the spatial and temporal constraint discussed above, the proposed prototypical patterns for *side-avoid* steering strategy can be specified as shown in Figure A.3.

Figure A.3: Situation and specification of the prototypical STPs corresponding to the *side-avoid* steering strategy.

The specification of this prototypical STP consists of one specified slice to reflect the spatial and temporal constraint as discussed (Figure A.3(b)). Similar to the prototypical STP for the overtake steering strategy, only the left half of the slice is specified due to the symmetric features of the vision and the matching process in our model. A range is identified to indicate the central area in front of the pedestrian, where the spatial constraint SC_1 is reflected as the sections with values “0-1”. The “-1” indicates the blockage caused by other pedestrian moving in the general opposite direction, and the “0” indicates the space beside for the pedestrian’s deviation when executing the steering strategy as shown in Figure A.3(b). Such spatial constraints exist at the current frame t_0 . Since the relative speed of two agents moving towards each other is large, and some pedestrians tend to start deviating earlier than others as observed in real life situations, we also define the other two similar prototypical STPs as shown in Figure A.3(c) and A.3(d). Such patterns indicate similar spatial

constraints SC'_1 and SC''_1 as SC_1 , but with the obstacles perceived in further attention ranges with no blockage in between. In such a case, where multiple prototypical STPs can trigger a steering strategy, different probabilities are assigned to these prototypical STPs in order to trigger the steering strategy. For example, the probability of triggering the *side-avoid* steering strategy by the prototypical STP shown in Figure A.3(b) is higher than the ones as shown in Figure A.3(c) and A.3(d) since people tend to resolve collisions by adopting the strategy more urgently in this case.

Appendix B

Supplementary Details of Results

In the result chapter (see Chapter 7), the validation process of the PBS model through three stages have been discussed. More details on the collected experimental data and the simulation results of models under the selected scenarios in the first stage of the validation process are provided in this appendix to supplement the discussions in the result chapter.

B.1 Supplementary Experimental Data

Supplementary experimental data and analysis of the experimental study is provided in this section.

B.1.1 Cat 1.1

In Cat1.1, participant 2 avoids the other two from the left side. The instantaneous speeds of each participant at each frame is plotted in Figure B.1. The speed curves indicate that all the participants reached a stable average speed of 1.5 m/s after the initial 40 frames. Such information can be used in the model initialization for the simulation experiments. The speeds of the two participants (see s'_1 and s'_3 in Figure B.1) are similar along the whole moving course.

To quantitatively measure the deviation in terms of the angular change of the moving direction, local slope of the fitted curve of a trajectory is examined as shown in Figure B.2. The local slopes of a participant's trajectory are indicated as the marked lines and the differences between the local slopes of each pair of participants are shown as the stacked bars. It is observed that the local slopes of participants 1 and 3 are more correlated with smaller difference (see ΔLC_{13} in Figure B.2) than any other pair of participants. This is particularly true between frame 30 and 80, when the deviation occurs.

Figure B.1: Speed of participants under Cat1.1.

Figure B.2: Local slopes and the differences between each two participants under Cat1.1.

Figure B.3: Distance between each two participants under Cat1.1.

Participants 1 and 3 maintain a short distance (see d_{13} in Figure B.3), while the deviation distances of the two participants (see dd_1 and dd_3 in Figure B.4) change in a more similar way compared to that of participant 2 (see dd_2).

Figure B.4: Deviation distance from the horizontal direction line under Cat1.1.

B.1.2 Cat 1.2

In Cat1.2, participant 2 avoids the other two from the right side. The average speeds of the participants under this category are drawn in Figure B.5. The significant variation of the curve during the last 40 frames (see s_1 , s_2 and s_3) could be due to the speed variances of participants from different sessions and the noise introduced at the image processing procedure. Given the smaller sample size as compared to Cat1.1 (40% of all sessions vs. 55% for Cat1.1), the effect of noise reduction is less significant in this category. Nevertheless, we could observe that the average speed of the three participants (see s'_1 , s'_2 and s'_3) are relatively consistent, similar to our observation in Cat1.1.

Figure B.5: Speeds of participants under Cat1.2.

The local slopes and the difference between those of each two participants are plotted in Figure B.6. It shows similar changing patterns for the local slope (see lc_1 , lc_2 and lc_3) and the differences (see ΔLC_{31} , ΔLC_{32} and ΔLC_{12}) as observed in Cat1.1.

Figure B.6: Local slopes and the differences between each two participants under Cat1.2.

Figure B.7: Distance between each two participants under Cat1.2.

For example, ΔLC_{31} is the smallest in both categories. Since a negative value of local slope indicates a deviation angle to the right, lc_1 , lc_2 and lc_3 are negative most of the time before participants 1 and 3 cross participant 2 (i.e., prior to frame 80).

From the perspective of the relative position and distance between participants, the data is also consistent with that of Cat1.1. The distances between each two participants are shown in Figure B.7 and the deviation distances of participants from the horizontal direction line are shown in Figure B.8. Participant 1 and 3 maintain a short distance (see d_{13} in Figure B.7) through the whole session. All participants start to deviate early (see dd_1 , dd_2 and dd_3 in Figure B.8).

B.1.3 Cat 1.3

In Cat1.3, participant 2 passes participant 1 and 3 from the space between them. The speeds of participants are shown in Figure B.9. We first observe the larger speed of

Figure B.8: Deviation distance from the horizontal direction line under Cat1.2.

participant 2 (see s_2). Secondly, s_2 and s'_2 reduce significantly at the last phase (after frame 110). This is due to the fact that participant 2 was moving faster than the other two, thus she reached the destination earlier and thus reduced her speed when approaching to the destination during the last 20 frames as reflected from the figure.

Figure B.9: Speeds of participants under Cat1.3.

Figure B.10 shows the local slopes and the difference between each two participants. It is observed that the local slopes of participant 1 (see lc_1) and 3 (lc_3) are not so closely correlated (see ΔLC_{31}) as compared to the previous two categories. lc_3 has the largest magnitude in this case, instead of lc_2 in the previous two categories. Such data indicates that participant 3 proactively gave way in this case. The deviation distance away from the horizontal direction lines for each participant is shown in Figure B.11. It is noted that participant 3 starts to deviate more significantly (see dd_3) from the beginning of the session compared with the others, which may also indicate that participant 3 initiated the interaction.

Figure B.10: Local slopes and the differences between each two participants under Cat1.3.

Figure B.11: Deviation distance from the horizontal direction line under Cat1.3.

The distances between each two participants are shown in Figure B.12. There are two differences observed when compared with the previous two categories. First, the bottom of the curves (see d_{12} and d_{23}) occurs about 15 frames earlier (at around frame 65 in this category comparing with around frame 80 in Cat1.1 and Cat1.2), which suggests that the three participants are moving faster. Such an observation is consistent with the observation of the faster moving speed of participant 2 (see s_2 in Figure B.9). Secondly, at the bottom of the curves (around frame 65), the distances between participant 1 and 3 (d_{13}) is the largest. Such an observation contradicts with some previous pedestrian studies, which suggest that “pedestrians prefer to maintain their personal space most of the time by avoiding close contact with others” [54]. By considering the three participants as a whole system during their interactions, interaction category Cat1.1 and Cat1.2 seem more consistent with the idea of personal space reservation as pointed out by the previous studies.

Figure B.12: Distance between each two participants under Cat1.3.

B.1.4 Cat2.1 and Cat2.2

In this scenario, participant 2 overtakes participant 1 and 3 from either their left (Cat2.1) or right (Cat2.2) side. The average speed of participants are plotted in Figure B.13 and B.14 for the two categories respectively. The faster speed of participant 2 (see s_2) is obvious, while the speeds of the other two participants (see s_1 and s_3) are quite consistent. The distance between each pair of participants for the two categories are shown in Figure B.15 and B.16 respectively. It is observed that participant 1 and 3 maintained the relatively short distance (see d_{13}) when initialized. The distances between participant 2 and the other two participants (see d_{12} and d_{23}) gradually reduces as she catches up; and the distances increase again as she passes over the other participants. A difference between Cat2.1 and Cat2.2 can be reflected through the relative positions between d_{12} and d_{23} .

Figure B.13: Speeds of participants under Cat2.1.

The local slopes of participants for both Cat2.1 and Cat2.2 are shown in Figure B.17 and B.18 respectively. It is observed that the local slope of participant 2 (see lc_2)

Figure B.14: Speeds of participants under Cat2.2.

Figure B.15: Distances between each two participants under Cat2.1.

Figure B.16: Distances between each two participants under Cat2.2.

is positive in Cat2.1 and negative in Cat2.2 most of the time, indicating the deviation to the left and right side during the overtaking process accordingly. In both categories, the local slope differences between participant 2 and the other two participants (see ΔLC_{12} and ΔLC_{32}) are larger than the difference between participant 1 and 3 (see ΔLC_{31}).

The deviation distance from the horizontal direction line of each participant is

Figure B.17: Local slopes and the differences between each two participants under Cat2.1.

Figure B.18: Local slopes and the differences between each two participants under Cat2.2.

Figure B.19: Deviation distance from the horizontal direction line under Cat2.1.

plotted in Figure B.8 and B.20 respectively for Cat2.1 and Cat2.2. It is observed that participant 2 starts to deviate early (i.e., almost from frame 0) with significant deviation (see dd_2), while the other two participants do not exhibit obvious deviation (see dd_1 and dd_3).

Figure B.20: Deviation distance from the horizontal direction line under Cat2.2.

B.1.5 Cat3.1

In this scenario, participant 2 remains behind participant 1 and 3 due to the spatial constraints. The speeds of participants along time are plotted in Figure B.21. It is observed that participant 2's speed (see s_2) is initially much larger than that of the other participants (see s_1 and s_3) as a reflection of their natural preferred moving speed through the initial screening. s_2 then gradually reduces to match with s_1 and s_3 . s_1 and s_3 are quite consistent through the whole session. Similar to scenario two, participants (1 and 3) seem to not interact with participant 2, who is reducing her speed to match with them.

Figure B.21: Speeds of participants under Cat3.1.

The local slopes of participants along the smoothed trajectories are shown in Figure B.22. It is observed that the local slopes (see lc_1 , lc_2 and lc_3) for the trajectory of all the participants are relatively small.

The distances between each two participants in this scenario is shown in Figure B.23. It is observed that participant 2 gradually gets closer to the two participants in

Figure B.22: Local slopes and the differences between each two participants under Cat3.1.

Figure B.23: Distances between each two participants under Cat3.1.

the front until a moment (i.e., around frame 120), when she remains behind the other two within a distance (around 0.5 m).

The deviation distance from the horizontal direction line is relatively small for all the participants as shown in Figure B.24. The increase of the deviation distance for participant 2 (dd_2) reflects her preference to following towards one side (participant

Figure B.24: Deviation distance from the horizontal direction line under Cat3.1.

3 in this case) behind the participants in the front.

B.2 Supplementary Simulation Results

B.2.1 RVO2 Model

To assess and compare the simulation results with the experimental data quantitatively, we process the simulation results under each scenario and measure the same metrics as previously discussed.

B.2.1.1 *Side-Avoid* Scenario

The speeds of agents are shown in Figure B.25. Agt_2 reduces its speed (see s_2) (from 1.5 m/s to 1.15 m/s) from frame 23 and remains at the speed of 1.15 m/s until frame 72, when the three agents complete avoiding collisions. Such an obvious speed drop of Agt_2 is inconsistent with the experimental data, where the speeds of all participants are relative constant during the interaction process. Other metrics, such as the local slope of each agent (see Figure B.26), distance between each two agents (see Figure B.27), and the deviation distance of each agent from the horizontal direction line (see Figure B.28), are measured and listed in corresponding figures.

Figure B.25: Speeds of agents in the RVO2 model under the *side-avoid* scenario

B.2.1.2 *Overtake* Scenario.

The speeds of agents are shown in Figure B.30. It is observed that the speed of Agt_2 reduces from frame 61 until frame 124. As a result, the agent takes more frames than the experimental data to overtake the other two agents in this case as can be found in the trajectories (see Figure 7.37).

Figure B.26: Local slopes and the differences between each two agents in the RVO2 model under the *side-avoid* scenario.

Figure B.27: Distance between each two agents in the RVO2 model under the *side-avoid* scenario.

Figure B.28: Deviation distance from the horizontal direction line in the RVO2 model under the *side-avoid* scenario.

The directional change of agents in the interaction process is reflected through the local slopes of their trajectories as shown in Figure B.29. The symmetry in the deviation of Agt_1 and Agt_3 is reflected by the local slope of their trajectories (see lc_1 and lc_3 in Figure B.29); the identical distance between Agt_2 and the two agents (see

d_{12} and d_{32} in Figure B.31) and the deviation distance of the two agents (see dd_1 and dd_3 in Figure B.32).

Figure B.29: Local slopes and the differences between each two agents in the RVO2 model under the *overtake* scenario.

Figure B.30: Speeds of agents in the RVO2 model under the *overtake* scenario.

Figure B.31: Distance between each two agents in the RVO2 model under the *overtake* scenario.

Figure B.32: Deviation distance from the horizontal direction line in the RVO2 model under the *overtake* scenario.

B.2.1.3 Follow Scenario

The steering behaviors of agents in terms of the directional changes are shown through the local slopes of their trajectories in Figure B.33; and in terms of the speed changes as shown in Figure B.34. The distance between each pair of agents is shown in Figure B.35, and the deviation distance of each agent from their horizontal direction lines are shown in Figure B.36. The figures illustrate the perfect symmetry in the deviation of Agt_1 and Agt_3 .

Figure B.33: Local slopes and the differences between each two agents in the RVO2 model under the *follow* scenario.

B.2.2 Social Force Model

B.2.2.1 Side-Avoid Scenario

In this scenario, Agt_2 avoids the other two agents from the space in the middle of them. The speeds of agents are shown in Figure B.37. Agt_2 reduces its speed (see

Figure B.34: Speeds of agents in the RVO2 model under the *follow* scenario.

Figure B.35: Distance between each two agents in the RVO2 model under the *follow* scenario.

Figure B.36: Deviation distance from the horizontal direction line in the RVO2 model under the *follow* scenario.

s_2) significantly (from 1.5 m/s to 0.1 m/s) at frame 62. Such an obvious speed drop during the interaction is inconsistent with the experimental data.

Similar to the simulation results of the RVO2 model, it is observed that Agt_1 and Agt_3 behave in a perfectly symmetric manner. It can be reflected from the distances between each two agents as shown in Figure B.39, where the distance between Agt_1

Figure B.37: Speeds of agents in the Social Force model under the *side-avoid* scenario.

Figure B.38: Local slopes and the differences between each two agents in the Social Force model under the *side-avoid* scenario.

Figure B.39: Distance between each two agents in the Social Force model under the *side-avoid* scenario.

and Agt_2 (d_{12}), and the distance between Agt_2 and Agt_3 (d_{32}) are perfectly identical throughout the simulation. The symmetry can be also reflected from the deviation distance of each agent (see Figure B.40) and the local slope and their differences between each two agents (see Figure B.38). These figures indicate that the simulation results of the SF model are quite similar to the RVO2 model in this scenario.

Figure B.40: Deviation distance from the horizontal direction line in the Social Force model under the *side-avoid* scenario.

B.2.2.2 Overtake Scenario

In this scenario, Agt_2 overtakes the other two agents in the front from the space in the middle between them. The speeds of agents are plotted in Figure B.41. The directional changes of agents in the interaction process are reflected through the local slopes of their trajectories, as shown in Figure B.42. The distances between each pair of agents are shown in Figure B.43, and the deviation distance of agents as shown in Figure B.44. It is observed that such metrics are much similar to the results of the RVO2 model in the same scenario as previously discussed.

Figure B.41: Speeds of agents in the Social Force model under the *overtake* scenario.

B.2.2.3 Follow Scenario

In this scenario, Agt_2 follows behind the other two agents through the whole simulation run. The change of agents' direction are reflected through the local slopes of their trajectories as shown in Figure B.45. Their speeds are shown in Figure B.46. It is observed that the speed (see s_3) and the local slope (see lc_3) of Agt_3 fluctuates

Figure B.42: Local slopes and the differences between each two agents in the Social Force model under the *overtake* scenario.

Figure B.43: Distance between each two agents in the Social Force model under the *overtake* scenario.

Figure B.44: Deviation distance from the horizontal direction line in the Social Force model under the *overtake* scenario.

corresponding to the bounces observed in trajectories. Since Agt_2 is closer to Agt_3 , its speed (see s_2) is affected and changes reversely with s_3 . The distance between each pair of agents is shown in Figure B.47, which is generally consistent with the experimental data. The deviation distance of each agent is shown in Figure B.48. It is

observed that dd_1 and dd_3 are larger than dd_2 , which is different from the experimental data.

Figure B.45: Local slopes and the differences between each two agents in the Social Force model under the *follow* scenario.

Figure B.46: Speeds of agents in the Social Force model under the *follow* scenario.

Figure B.47: Distance between each two agents in the Social Force model under the *follow* scenario.

Figure B.48: Deviation distance from the horizontal direction line in the Social Force model under the *follow* scenario.

Appendix C

Supplementary Details of Hypothesis Test

In Section 7.1.3, we concluded that the difference between the interaction categories Cat1.1 and Cat1.2 is insignificant based on the observed samples of participants' movements in the *side-avoid* scenario. In the scenario, the total sample size is 20, with 11 samples of Cat1.1, 8 samples of Cat1.2 and 1 case of Cat1.3. Our hypothesis is:

H: “the probability of Cat1.1 is significantly higher than that of Cat1.2.”

Note that this is a one-tail event hypothesis. The null hypothesis is defined as:

*H*₀: “Cat1.1 and Cat1.2 are not significantly different.”

In other words, they have the same probabilities p_1 and p_2 being taken from N samples: $p_1 = p_2$. Over multiple samples, the probability of p ($p = p_1 - p_2$) should follow a normal distribution with the mean of 0.

For Cat1.1 to appear K times ($0 \leq K \leq N$), the probability massive function is:

$$p_1(K) = C_N^K p_1^K (1 - p_1)^{N-K} \quad (\text{C.1})$$

where $C_N^K = \frac{N!}{K!(N-K)!}$

Assume $p_1(K)$ follows a normal distribution (μ_1, σ_1) for $K = 0, 1, 2 \dots N$. Then its mean: $\mu_1 = N \cdot p_1$ and the variance $\sigma_1 = N \cdot p_1 \cdot (1 - p_1)$.

Similarly, for Cat1.2 to appear K times ($0 \leq K \leq N$), the probability massive function is:

$$p_2(K) = C_N^K p_2^K (1 - p_2)^{N-K} \quad (\text{C.2})$$

Similar to $p_1(K)$, $p_2(K)$ follows a normal distribution (μ_2, σ_2) for $K = 0, 1, 2 \dots N$ with the values: $\mu_2 = N \cdot p_2$ and $\sigma_2 = N \cdot p_2 \cdot (1 - p_2)$.

Since p_1 and p_2 are independent, probability $p (= p_1 - p_2)$ follows a normal distribution of (μ, σ) with the mean and standard deviation as:

$$\mu = \mu_1 - \mu_2 \quad (C.3)$$

$$\sigma = \sigma_1 + \sigma_2 \quad (C.4)$$

Substitute Equation C.1 and C.2 into C.3 and C.4 we get:

$$p(Np_1 - Np_2, Np_1(1 - p_1) + Np_2(1 - p_2)) \quad (C.5)$$

In our experiments, $N = 19$ considering only the probabilities of Cat1.1 and Cat1.2, thus:

$$p(0, 19 \times 0.5 \times (1 - 0.5) \times 2) = (0, 9.5) \quad (C.6)$$

Standardize p to normal distribution with $(0,1)$ to get the Z score as:

$$Z(p) = \frac{(x_1 - x_2 - 0)}{\sqrt{9.5}} = \frac{11 - 8}{3.0822} = 0.9733 \quad (C.7)$$

Through checking the standard distribution table, we find that the total area under the distribution to the left of the Z score is 83.7%. The p value in this case is 0.123 for a one-tail event under our hypothesis. Since the p value is larger than 0.1 (under the assumed significance level of 90%), the null hypothesis can not be rejected.

In summary, based on the observations from the experiments, we can not conclude the probability of Cat1.1 is significantly larger than Cat1.2. Thus, their difference is insignificant with the significance level of 90%.