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NANYANG
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**CONCEPTUAL FRAMEWORK AND ALGORITHMS TO
CLASSIFY WANDERING TRAVEL PATTERNS OF
ELDERLY WITH DEMENTIA**

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SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

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WITH DEMENTIA**

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Abstract

Wandering is one of the most common behavioral disturbances among people with dementia (PWD). Sensing and localization technologies have been used in wandering management, especially elopement prevention. However, little research has been focused on measuring wandering behavior and not many applications in wandering management are widely used in practice due to two reasons. First, technologists' understanding and perception of wandering do not align with those of gerontologists. This consequently lowers the chance of proposed solutions to be accepted for clinical research and applications. Second, most solutions do not address all the dimensions of dementia wandering nor do they cater to the needs of other stakeholders involved including caregivers, physicians and researchers.

The contributions of this thesis are two-fold. We first present a conceptual map of wandering science from the perspectives of gerontologists. Then we provide a framework which identifies main threads of technologies that can be further developed to manage dementia wandering. We further discuss research and design issues, human factors, ethical concerns, security and privacy that need to be considered when implementing solutions for wandering management.

Second, we develop pattern recognition methods to identify and classify travel patterns automatically from sensor data. According to gerontologists, this is the first key step in any specific investigation of dementia wandering and subsequently measuring wandering behavior. In this thesis, we design and develop two discriminative algorithms to classify dementia-related travel patterns using different sensor modalities. The first algorithm uses spatial and temporal information from location sensors and the second one uses inertial information from inertial sensors. We have evaluated the performance of our developed algorithms on real world datasets of both dementia and non-dementia subjects. A comparison of our algorithms' performance with one of classical machine learning classifiers, Markov models, and time series classification algorithms such as Symbolic Aggregation Approximation (SAX) and Dynamic Time

Warping (DTW) shows that our algorithms outperform other classifiers from 5% to 26% in terms of classification recall and 51 to 739 times faster in terms of classification processing time.

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List of Abbreviations

ABBREVIATIONS

ALF

BAG

DTW

GIS

k-NN

LB

MLP

MMSE

MS

NB

PAA

PWD

RF

RFID

RSAX

RSSI

SAX

SVM

UWB

FULL EXPRESSIONS

Assisted Living Facility

Bagging

Dynamic Time Warping

Geographic Information System

k-Nearest Neighbor

Logiboot

Multilayer Perceptron

Mini-mental State Examination

Martino-Saltzman

Naïve Bayes

Piecewise Aggregate Approximation

People With Dementia

Random Forests

Radio Frequency Identification

Reverse-SAX Based Algorithm

Received Signal Strength Indicator

Symbolic Aggregation Approximation

Support Vector Machine

Ultra Wideband

In this chapter, we present the background and motivation of our research, our contributions to the field, and the outline of the thesis.

1.1 Background: the need for managing wandering behavior

Wandering is generally described as a form of locomotion, most often repetitive walking or aimless meandering [1]. In clinical settings, wandering behavior seems to happen most commonly to PWD. The prevalence of PWD who wander was reported to be as high as 63% and the incidence is found to be greater in people with Alzheimer's disease than in those with vascular dementia [2]. Unsafe wandering increases the risk for falls, hip fractures, sleep disturbances, getting lost, elopement and death [3-7]. In the USA, 70% of legal claims filed against nursing homes are related with the wanderers' deaths [8]. Currently, there is no pharmacological treatment that can completely cure wandering. Some wanderers are given psychoactive medications to reduce wandering; however, it often leads to unpleasant side effects [9] and creates an ethical dilemma for caregivers [10]. Managing wandering of PWD has thus become an increasingly imperative problem for caregivers and policymakers due to the rapidly soaring number of demented persons. Statistical studies indicate that the number of PWD worldwide will quadruple to 115 million by 2050 [11] and account for nearly \$640 billion in total direct and indirect costs annually [12].

In practice, family members and professional caregivers find it stressful to cope with wandering behavior and with the need to multi-task in order to look after PWD. In a survey of caregivers for PWD, staff listed wandering as one of the top three most difficult behavior problems to manage [13]. The level of caregiver's burden is significant; with 27.2% of caregivers expressing feelings of burden more often than sometimes especially when this behavior occurs several times a day [14]. If the wandering patient is managed properly, staff will experience lower frustration and more tolerant attitudes toward the patient

[13]. On the other hand, caregivers have to cope with the guilt of not doing enough and the burden of feeling personally responsible for PWD probably due to the lack of awareness and knowledge on negative effects and consequences of wandering to the patient's well-being. Helping caregivers juggle multiple responsibilities and supporting them through feelings of guilt and not being up to the task is therefore the key to dementia care.

In addition, managing wandering behavior will play an important role in diagnosis and assessment of dementia. First of all, a review of the literature suggests that wandering potentially be used as a diagnostic sign for preclinical dementia [15-17]. A five-year study of clinical records in patients with preclinical dementia [15] found that wandering is the earliest symptom followed by cognitive complaints. There is evidence to show that changes in locomotion patterns begin many years prior to the onset of dementia [16] and gait-related motor disturbances present in all subtypes of dementia, even in the early and preclinical stages [17-18]. Early detection of such changes will call for early treatment of dementia and prolong the onset of the disease. This will improve the person's quality of life and delay the transition to costly care facilities.

Secondly, evidence-based research reveals that several features of wandering are associated with cognitive declination, health status, and other physiological effects in PWD. Patients with mild cognitive impairment were found to have greater variability in walking speeds and activity levels than those without the diagnosis [19-20]. Increased stride time variability is also correlated negatively with cognitive performance and increased the risk for falls in community-dwelling elders [21-22]. Algase et al. [23] found that pacing patterns among PWD who wander are signals of agitation and discomfort. It is therefore essential to quantify and measure wandering in PWD in order to identify and address the declines in cognitive function indicative of dementia or other negative health states.

Lastly, as wandering is associated with negative sequelae such as falls, getting lost, or elopements from home or care environments, wandering monitoring systems will provide timely alerts and emergencies to caregivers or family members and promise to prevent such detrimental outcomes from happening.

1.2 Motivations

Dementia wandering is a subject of study and research in the field of gerontology for more than 3 decades. The topic has then drawn the attention of technologists and particularly computer scientists since early 2000. Though a number of solutions and applications have been proposed and implemented to manage wandering, not many are widely used in practice due to 2 reasons.

First, technologists' understanding and perception of wandering do not align with those of gerontologists. This is proved by the use of dementia-related terms and definitions in technological works. In fact, terms such as "wandering", "wandering outcomes", "wandering correlates" (e.g. shadowing, lingering near exits) are often used interchangeably in technological studies. However, they do not necessarily mean the same thing. In addition, wandering is defined differently in different works. For example, Kim [24], Miskelly [25], and Patterson [26] aimed to detect dementia wandering. Kim measured the time a person spending in his/her room and around other rooms to reason if a person is wandering. Miskelly considered a person wandering if he/she moves out of a designated zone whereas Patterson detected wandering by tracking if a person strays from a predefined route. Clearly, wandering means differently in these 3 works. All 3 works claimed to detect dementia wandering; however, in gerontological perspective, Kim, Miskelly, and Patterson just respectively addressed the temporal distribution, boundary transgression, and spatial disorientation dimensions of dementia wandering. It is questionable if technologists are aware of the differences of these wandering dimensions. A more critical question is whether technologists in general share the same perception on wandering and its dimensions with gerontologists. In gerontology, dementia wandering is a complicated behavior encompassing time, space, geographical patterns,

negative outcomes, and the drive or impetus for wandering [27]. Technologists tend to rely on their own perception of wandering to recognize and manage it, which is much simpler than the one of gerontologists. This consequently lowers the chance of proposed solutions to be accepted for clinical applications.

Second, most solutions do not address all the dimensions of dementia wandering. The present capacities of such systems are predominantly to track and provide the position of a wanderer at any moment. For example, GPS-based devices and products like Em Finder [28], GPSShoes [29] let caregivers monitor a person with dementia outside the home or formal care environments. Complex systems like Lifeline 4000+ home reassurance unit [30] address the safety and security for PWD, i.e. ensure that PWD remain in designated safe zones or are easily located if they do move away from these areas. Other ambient systems with ultra wideband and radio frequency identification (UWB-RFID) technology can locate wanderers before or after elopement in indoor environments like nursing home [31]. Research projects [32-35] in this area are primarily focused on the employment of body-attached sensors or communication technologies such as GPS, GSM, GIS, or RFID to remotely monitor dementia patients. Their abilities to characterize, identify wandering and detect negative consequences associated with wandering are still limited. Few applications cater the needs of other stakeholders involved including caregivers, physicians and researchers.

This research aims to:

- Bridge the knowledge gaps between gerontologists and technologists by presenting a conceptual map of wandering science from the perspectives of gerontologists, which is studied in Chapter 2
- Develop reliable and efficient algorithms to address one of the most critical needs of gerontology researchers which is to capture geographical or travel patterns of dementia and non-dementia wandering, which is studied in Chapter 4 and 5. To the best of our knowledge, we are the first

group who aims to develop automated algorithms to classify travel patterns of people with dementia

1.3 Contributions

The contributions of this research are summarized as follows:

- First, we generate a conceptual map of wandering and create a technological framework for wandering management. We simplify and synthesize available materials on wandering science from gerontological perspective to generate a conceptual map of wandering that covers all domains of dementia wandering. The conceptual map provides researchers, especially technologists with comprehensive and organized perspectives on the dementia wandering literature. This is complemented by the technological framework, which provides researchers, especially non-technologists with good knowledge of potential technologies that may be harnessed for wandering studies and management. Harnessing assistive technologies to manage dementia-related wandering is a new and emerging field of research. Not many proposed solutions could meet the needs of gerontologists. It is crucial to incorporate important findings and lessons from relevant literature for a technology solution to be feasible and to succeed. The map and framework not only encapsulate such findings uncovered in the process of our comprehensive literature review, they also help to organize the diverse literature from both healthcare and technology perspectives. We strongly believe the map and framework will provide valuable guidance for technologists to further develop assistive applications and tools that are relevant for effective wandering management.
- Second, we are the first group who automate the detection and recognition of dementia-related wandering patterns. We have developed a predefined tree-based computer algorithm to classify travel patterns (direct, pacing, lapping, and random) exhibited by persons with dementia (PWD)

living in dementia care units. Traditionally, wandering patterns are classified by observational methods in which researchers videotape the movements of PWD, then manually classify these patterns by visually inspecting the recorded movements. Studies were limited by such labor intensive observation methods which are susceptible to human error. Moreover, informed consent is required as visual observation is considered invasive of a subject's privacy. Consequently, very few works in the literature engaged PWD as test subjects thus only limited data are available for meaningful studies on wandering. By removing the obstacles of observation methods, we believe it will encourage more research studies to better understand dementia-related wandering. This contribution is also significant because our classification algorithm is tested on data sets representative of patients with various stages of dementia. In terms of performance, the algorithm improves the classification accuracy by 5.9% to 98.2% and significantly reduces the classification latency to 0.0003s when compared with traditional machine learning classifiers. In terms of applicability, the classification algorithm is deployed on a mobile phone to demonstrate its real time ability to provide caregivers with alerts as soon as a PWD wanders. This is significant in enabling caregivers to provide timely assistance and interventions to the PWD.

- Third, we also created a representation of time-series orientation signals called reverse-SAX and proposed a new classifier which is based on the reverse-SAX representation and the logic of the predefined tree-based algorithm. We present and implement a new method to collect and classify wandering patterns using mobile and wearable devices. The new method of data collection is cheaper and more readily available compared to those using video cameras, RFID or UWB localization systems. The method is not intrusive; the orientation data collected from subjects both with and without dementia have sufficiently high quality for the analysis of wandering patterns. For wandering patterns classification, we have created a representation of time-series

orientation signals called reverse-SAX and proposed a new classifier based on this representation and the predefined tree-based algorithm. The new classifier is superior to other time-series classification approaches such as SAX and DTW. The classifier is tested on orientation data collected from subjects both with and without dementia. Average classification recall of 84.89% and 88.5% are obtained in a controlled and an uncontrolled study, respectively. The classifier requires no prior training; it takes approximately 7.4 milliseconds to classify a travel episode and approximately 0.15 seconds to classify the whole test datasets. This is significant in providing a non-intrusive, real-time, effective solution that has overcome all the obstacles of video camera-based observation methods that gerontologists have traditionally used in dementia-related wandering research.

1.4 Organization

The rest of this report is organized as follows:

- Chapter 2 discusses the conceptual map and technological framework of wandering science.
- Chapter 3 reviews the existing technological systems for wandering management.
- Chapters 4 focuses on the predefined tree-based algorithm to classify wandering patterns using location information.
- Chapter 5 introduces the new representation of time-series signals for wandering detection. It also presents the developed classifier to identify travel patterns including wandering using inertial sensors data. The results of the controlled and uncontrolled studies on non-dementia and dementia subjects are reported.
- Chapter 6 concludes the report and discusses future work.

Chapter 2 Conceptual Map and Technological Framework of Wandering Science

This chapter first presents a concise conceptual map of wandering science. Second, it discusses the technical framework identifying main threads of technologies for managing dementia-related wandering.

2.1 Motivations for the conceptual map and the technological framework to manage wandering

The conceptual map of wandering science is to answer the 6 fundamental questions related to wandering behavior: Who is involved in it? What constitutes it? Where does it occur? When does it occur? Why does it occur? How to intervene it?

The purpose of introducing this overall conceptual map is three-fold. Firstly, it provides the essential fundamental background on dementia-related wandering. This will enable a mutual understanding of wandering in the scientific community and especially in the computer scientists' community. Secondly, it serves as the basis for the technological framework that we create in order to identify the kinds of technologies that can be developed to assist wandering management.

Thirdly, we would like to promote wandering science from the perspective of gerontologists to technologists. There are two reasons why this is important. First, technologists tend to rely on their own perception of wandering to recognize and manage it. And their perception of wandering is much simpler than the one of gerontologists. In fact, more than 90% of technological works focus on outcomes (e.g. elopement, getting lost) of wandering behavior. Terms including wandering, wandering outcomes, wandering correlates (e.g. shadowing, lingering near exits) are often used interchangeably in these studies. These technologists are likely not aware of the differences and therefore they do not cover all aspects or dimensions of wandering in designing and developing assistive technologies. Second,

technologies are created to assist PWD, caregivers, and gerontologists. Thus, it is important for technologists to identify the needs of these stakeholders and base on widely utilized concept of wandering to develop assistive applications. It will then maximize the likelihood of their technologies' acceptance in reality.

2.2 Conceptual map of wandering science

Figure 2.1: Overall Conceptual Map of Dementia-Related Wandering

Fig. 2.1 depicts the conceptual map and briefly answers 6 interrelated questions (domains) on wandering behavior. In each domain, we provide a concise description and identify potential assistive technologies that can be developed.

2.2.1 WHO Domain

2.2.1.1 Who is involved in dementia wandering?

The WHO domain refers to the stakeholders of dementia wandering. It includes PWD, direct caregivers (family members or nurses), researchers and clinicians. In the conceptual map, PWD is encapsulated and referred by solid arrow because wandering directly affects them. Other 2 groups of stakeholders are

referred by dash arrows because wandering indirectly affects them. Caregivers are placed additional care burden due to the extra time needed to surveillance the behavior. Clinicians are challenged to monitor the occurrence and progress of wandering in the long-term care settings as well as to find effective treatments and interventions. Researchers especially gerontologists face difficulties in conducting dementia wandering studies due to the lack of efficient methods to observe, assess, measure, and quantify wandering.

2.2.1.2 What are the potential assistive technologies for the WHO domain?

PWD need effective technological interventions to reduce wandering as well as exposure to negative outcomes. Caregivers can be equipped with assistive information services or applications to surveillance wanderers, ensure wanderers' safety and well-being. Clinicians require sensing and communication systems that record wandering behavior as well as changes in wandering indicative of cognitive decline or negative health status so that they can provide timely treatment. Gerontologists specifically need tools and means that enable them to conveniently observe, measure, and quantify wandering so that they can conduct massive, longitudinal studies on patients with various backgrounds and in different territories.

2.2.2 WHAT Domain

2.2.2.1 What is wandering?

What is wandering indeed? In fact, there is the lack of a universal, widely utilized definition of wandering within the gerontology discipline and across disciplines because it is a complex behavior and expressed in various forms over time and place, within persons, and across different people [36-38]. Table 2.1 summarizes 3 empirical definitions of wandering. The clinical definition [39], developed within nursing science as a nursing diagnosis almost a decade ago, has yet to be routinely seen in published wandering literature [40]. The policy-oriented definition [41] is used by policy makers and risk managers. It is meant for media reports of accidents, injuries, and deaths of wandering patients, and lawsuits related to charges

of unsafe wandering in institutional settings [42]. The scientific definition [43] was proposed in 2006 at the International Consortium for Research on Wandering on the basis of analysis and synthesis of terms and definitions from 183 published papers. It is recommended to adopt this provisional consensus definition in all scientific studies regarding dementia-related wandering because it allows others to independently verify the validity of research results through observation, measurement, or testing [42].

Table 2.1: Definitions of Dementia-Related Wandering

Definitions	Description
Clinical definition (NANDA, 2001)[39]	Meandering, aimless or repetitive locomotion that exposes a person to harm and is incongruent with boundaries, limits or obstacles.
Policy-oriented definition (VHA, 2002) [41]	A wandering patient is a high-risk patient who has shown a propensity to stay beyond the view or control of employees, thereby requiring a high degree of monitoring and protection to ensure the patient's safety.
Scientific definition (Algase et al, 2006) [43]	A syndrome of dementia-related locomotion behavior having a frequent, repetitive, temporally-disordered, and/or spatially disoriented nature that is manifested in lapping, random, and/or pacing patterns, some of which are associated with eloping, eloping attempts, or getting lost unless accompanied.

According to the scientific definition, wandering is measured in terms of *frequency* (a sum, mean, or rate of wandering episodes per unit time); *repetitiveness* (characterized by 2 items: wanderer goes repeatedly to the same location; wanderer travels repeatedly the same route while walking); *temporal distribution* (wandering duration between lunch and dinner; between breakfast and lunch; between dinner and bedtime; between waking and breakfast); *spatial disorientation* (characterized by 5 items: wanderer cannot locate dining room/own room/bathroom without help; wanderer bumps into obstacles or other people while walking alone; wanderer walks about aimlessly; wanderer gets lost); *geographical patterns* (wandering in pacing, lapping, random patterns); *eloping behavior* (characterized by 4 items: wanderer runs off; wanderer enters unauthorized area; wanderer attempts to leave authorized area; wanderer is returned to authorized area after leaving unnoticed); *negative outcomes* (characterized by: fatigue;

inadequate food intake; falls and injuries; exit attempts despite caregivers' efforts to keep wanderer in a location or home).

Table 2.2 lists the items constituting each wandering dimension. Nursing researchers and gerontologists use observation method to record and measure dimensions of wandering. Here is a brief description of the methodology. A respondent who is in direct contact with the wanderer will observe the wanderer's natural movements for a continuous observation period of 20-30 minutes. The respondent scores each item in each dimension on a scale from 1 to 5 (1=never or unable, 2=seldom, 3=sometimes, 4=usually, 5=always). The scores collected will be used to assess or study wandering behavior of PWD. Usually, a wanderer will be observed for a period of 2 weeks to 1 month or 6-12 months in longitudinal studies. Observations (or episodes) are separated by at least 48 hours. The information recorded will enable gerontologists to identify whether a patient with dementia is wandering.

Table 2.2: Wandering Dimensions

Dimension	Items
<i>Repetitiveness</i>	wanderer goes repeatedly to the same location; wanderer travels repeatedly the same route while walking
<i>Temporal distribution</i>	wandering duration between lunch and dinner; between breakfast and lunch; between dinner and bedtime; between waking and breakfast
<i>Spatial disorientation</i>	wanderer cannot locate dining room/own room/bathroom without help; wanderer bumps into obstacles or other people while walking alone; wanderer walks about aimlessly; wanderer gets lost
<i>Geo-patterns</i>	pacing; lapping; random patterns
<i>Eloping behavior</i>	wanderer runs off; wanderer enters unauthorized area; wanderer attempts to leave authorized area; wanderer is returned to authorized area after leaving unnoticed
<i>Negative outcomes</i>	fatigue; inadequate food intake; falls and injuries; exit attempts despite caregivers' efforts to keep wanderer in a location or home

2.2.2.2 What are the potential assistive technologies for the WHAT domain?

Technologies play a very important role in helping physicians and researchers characterize the WHAT domain. We divide such technologies into 3 categories. The first one is to measure *frequency*,

repetitiveness, and temporal distribution. The second one recognizes *spatial disorientation and geographical patterns.* The last category evaluates *eloping behavior and negative outcomes* associated with wandering. The first category could be actualized in the short term by basic sensing and simple computation systems. The second category requires research works incorporating pattern recognition and classification techniques. Elopement prevention can be achieved using available tracking and localization technologies whereas evaluating negative outcomes requires combinations of multiple disciplines and long-term research works.

2.2.3 *WHERE and WHEN Domains*

2.2.3.1 *WHERE and WHEN does wandering occur?*

We combine the WHERE and WHEN domains together because they are highly interdependent, i.e. it is possible to detect when wandering happens once we can detect where wandering happens. Wandering happens in both outdoor (community-dwelling) and indoor (nursing homes, home environments, assisted living facilities) settings. It usually occurs in the morning hours, increases in the amount and frequency throughout the day, and reaches the peak at 5-7 pm.

2.2.3.2 *What are the potential assistive technologies for the WHERE and WHEN domains?*

Knowing where and when a person wanders allows better arrangement of caregivers or facilities so as to improve quality of care. For instance, more staff should be arranged to look after PWD during dinner time if that is the period PWD wander the most; or if we know that open space halls could stimulate more wandering, we would place some stuffs there to limit PWD from wandering. Current tracking and localization applications such as GPS-enabled phones [25] or Ubisense tagging systems [31] can help determine where and when a person wanders. Such technologies are mature and stable. The availability of commercial products and various tracking applications on mobile platforms is clear evidence.

2.2.4 *WHY Domain*

2.2.4.1 *WHY does wandering occur?*

There are two groups of factors that account for wandering in PWD. Background factors consist of neurocognitive status, general health, and socio-demographic factors [44]. For example, a person may wander because he/she gradually loses memory and visual-spatial or orientation skills as dementia worsens; or because he/she is in pain due to earache, toothache or constipation; or because his/her previous jobs (deliverymen, salesperson, etc.) require him/her to travel and move around frequently. Proximal factors include personal need states, both physiological and psychological, and environmental conditions, both physical and social. For instance, wandering might be a search for food in response to hunger, or a way to cope with boredom or loneliness. Sometimes, ambient conditions (lighting, sound, or temperature within a location) or lack of social interaction in care and home environments could also trigger wandering [45].

2.2.4.2 *What are the potential assistive technologies for the WHY domain?*

We realize that background factors are complicated and constitute relatively stable, slowly changing characteristics of PWD which are hard to be intervened by technologies. It is more feasible for technologies to analyze proximal and environmental factors to detect and mitigate wandering because proximal factors are more dynamic features of the person and of the immediate environment.

2.2.5 *HOW Domain*

2.2.5.1 *HOW to intervene wandering?*

There are 4 approaches to intervene wandering.

Environmental modification involves modifying environmental features of the care settings to limit wandering. The 6 environmental features of long-term care units (suggested by research and practice literatures) that are associated with wandering behavior are: unit layout, hallways, doorways, unit exits,

directional and destination signage, and ambient conditions [46]. For example: place gridlines in front of exit doors, provide a secure wandering/walking area, make exits less accessible or noticeable, use a combination of large-print signs and portrait-like photographs to aid residents to find own bedrooms [47].

Behavioral techniques are the most commonly used and productive approach to limit wandering. Examples include: promote social interaction during structured activities, introduce music sessions or reading sessions, schedule regular exercise, or apply air mat therapy as well as aromatherapy [47-48].

Technology and safety systems can be used to intervene wandering. Alarm/alert and sensory devices are used to safeguard PWD and provide alerts to caregivers or family members when PWD elope or attempt to elope [49]. Mobile locator devices are used to quickly locate wanderers [50].

Pharmacological treatment may be considered when nonpharmacologic treatments fail. In fact, behavioral symptoms of dementia like wandering can be helped with nonpharmacologic approaches and do not respond well to pharmacologic treatment. There is limited evidence-based data available specifically on efficacy of pharmaceutical options (e.g. risperidone, olanzapine, citalopram, mirtazapine) on wandering even though these options are commonly used to treat symptoms like aggression or agitation [51].

2.2.5.2 What are the potential assistive technologies for the HOW domain?

There exist technology and safety systems to intervene wandering, e.g. alarm/alert and sensory devices, mobile locators. Future information services should be developed to guide caregivers. An example is a mobile application that provides recommended behavioral and environmental modification techniques for caregivers to target different wandering scenarios. Such applications can also contain videos, images, and scenarios showcasing different wandering behaviors of PWD. Direct caregivers can then learn and recognize wandering as well as provide immediate interventions. These applications will serve as

educational or training tools for caregivers who have limited knowledge of wandering and its associated outcomes.

2.3 Technological Framework to Manage Wandering

We analyze the needs and unavailability of technologies for managing wandering in each domain. In Fig. 2.2, we present a framework of technologies for managing dementia-related wandering. These technologies target the WHAT, WHERE, HOW, and WHY domains and serves 3 different application users (PWD, caregivers, clinicians and researchers) in the WHO domain. We do not exclude technologies targeting WHEN domain. Instead, we combine them with technologies targeting the WHERE domain because they are highly interdependent, i.e. it is possible to detect when wandering happens once we can detect where wandering happens. The framework consists of 3 building layers (user interface, applications & logic, sensing modalities) and 2 mediational layers (network & repository, data fusion).

Figure 2.2: Framework of Assistive Technologies for Managing Dementia-Related Wandering

The **SENSING MODALITIES** layer represents sensors that are deployed in assistive applications.

The DATA FUSION layer preprocesses data collected from sensors and provides inputs for the applications & logic layer. Common preprocessing steps include cleansing, filtering, smoothing, and re-sampling. Cleansing discards unused or malfunctioning data points, or trims trajectory data to define the start and end of wandering episodes. Filtering rejects corrupted readings from sensor data. Smoothing is applied to reduce and smooth-out short-term irregularity in the data series to reveal more clearly the underlying trend or characteristics in the data. Potential filters and smoothers for wandering data can be Maximum Redundant Distance filter, Kalman filter, weighted moving average or exponential smoothers. Fixed interval re-sampling may be required for data analysis if the collected data is sampled at irregular time intervals.

The APPLICATIONS & LOGIC layer consists 2 sub-layers: applications and logic. The logic sub-layer consists of algorithms to: track and locate wanderers; geo-fence and prevent elopement; provide assistive information services; measure 3 dimensions of wandering including frequency, repetitiveness, temporal distribution; recognize wandering patterns and spatial disorientation; and analyze proximal factors to detect wandering. These algorithms are pivotal to creating applications to provide navigation support for PWD when they disorient and get lost, to provide intervention cues for direct caregivers when PWD wander, to assist researchers and clinicians to realize negative outcomes and study background factors associated with dementia-related wandering. The direction of arrows in Fig. 2.2 shows the applicability of these applications.

The NETWORK & REPOSITORY layer consists of 2 modules: network and repository. Repository module is a database that stores the lists of navigation plans to support wanderers when they get disoriented. Also, it stores intervention cues that direct caregivers can perform to limit wandering. Additionally, it records measurements of wandering dimensions and changes in proximal factors. Network module is a networking communication platform based on a client-server architecture. It is used to facilitate communication between the applications layer with the application users.

The USER INTERFACE layer consists of 4 parts. The to-do list and navigation module is used to assist PWD to navigate through the navigation plan received from the to-do list repository. The interface shows information indicating the direction where the disoriented user is expected to go. The to-do list and interventions module suggests what caregivers can perform to intervene wandering. The interface shows lists of cues or tasks received from the to-do list repository. The progress reports module enable researchers and clinicians to generate reports of possible negative outcomes and affected background factors through monitoring and analyzing wandering dimensions and proximal factors. The interface shows graphs plotting dimensions of wandering throughout the day, week, or months. It also indicates or highlights changes in these dimensions and proximal factors. The communication module offers a communication channel between PWD, caregivers, researchers and clinicians. Its interface shows assistive buttons to enable calls for help and intervention.

Chapter 3 Literature Review

Technologies for managing dementia-related wandering are a subset of assisted living technologies. There have been excellent surveys of assisted living technologies for elderly and dementia people in the literature [52-56], in which wandering management was sporadically reviewed. These reviews only included technologies concerning the WHERE and HOW domains of wandering. Others that evaluate the WHAT and WHY domains of wandering were not summarized and synthesized. In this thesis, we first examine the WHERE and HOW domains by synthesizing those reviews with other works not yet included, followed by expounding on the WHAT and WHY domains of these works. All systems described in this thesis were designed for PWD unless otherwise stated.

From Fig. 2.2, we identify that the first 2 applications (navigation support and intervention cues) target the WHERE and HOW domains in the conceptual map (Fig. 2.1) and the last 2 applications (negative outcomes and background factors) target the WHAT and WHY domains respectively. As elaborated earlier, these applications can be developed by combining algorithms in the logic sub-layer. Therefore, in the next section, we categorize the existing technological work into the 6 groups of algorithms in the logic sub-layer. We will also review the application to study background factors separately but not the other 3 since they are addressed together with the 6 groups of algorithms. The chapter is ended with the highlight of what are the research directions in technologies for managing dementia-related wandering.

3.1 Using sensors to geo-fence and prevent elopement

The related works are categorized into 2 groups: alarm/alert and sensory systems. Both groups deploy sensors in home or care environments. Alarm/alert systems attach commercial alarms and alerts at exit doors to prevent wanderers from elopement whereas sensory systems employ a wide variety of low-cost sensors to evaluate indoor movements of PWD so as to ensure safety.

3.1.1 Alarm/Alert Systems

Alarm systems alert caregivers when the wanderer is detected to be leaving the monitored area. They may automatically lock doors or incorporate wireless technologies to trigger alarms [50]. Such systems are available in three forms. *Audible alarms* [49] sound when a monitored door is accessed by the tagged person. *Optically activated alarms* [57] activate lights via passive infrared motion detectors when a monitored door or area is accessed. *Video-activated alerts* [58] run continually and are activated by triggers and can provide real-time feedback. Audible and optically activated alarms are well-established, installable on interior and exterior doors, and nonrestrictive to locomotion. However, loud audible or even false positive alarms (e.g. when guests or caregivers access the monitored door or area) may be distressing. Video monitoring system [58] achieved 100% sensitivity but could not distinguish wanderer's elopements from routine exiting of the caregivers. In addition, the system can only cover confined area and has issues with privacy of monitored subjects.

3.1.2 Sensory Systems

Sensory systems [59-61] used different location modalities such as infrared sensors [59], optical illumination-based location sensors [60], or ultra-wide-band radio receivers with small tags for transmitters [61]. From the location information collected, subjects' movement trajectories are modeled to estimate covered distances and travel speeds [59] or anticipate dangerous situations that may happen when the wandering subjects enter adverse areas like exit doors or laundry rooms [60]. In addition, location data may be combined with other signals like the amount of social interaction and the quality of sleep [61] to monitor state changes of PWD. The limitation of these studies is they were not evaluated on large number of subjects. The evaluation of the correlation between sensory data and the development of the dementia in the inhabitants [61] has not yet been possible whereas [59] managed to get one wanderer involved in their trial for 8 months.

CareWatch [62] is a smart home system that uses motion, door opening and bed occupancy sensors to alert the caregiver of unattended home exits, particularly at night. The system has been randomly assigned to 27 homes with dementia subjects for trial. Although the final results have not yet been published, CareWatch has operated for more than 200 months of combined system time (of 27 homes) without any major failures [54]. Moreover, there have been no unattended exits during the night in homes instrumented with CareWatch.

In short, audible and optically activated alarms are commercially available. They offer quick and simple solutions to prevent wanderers from eloping. However, the problem of these solutions is false positive alarms. Video-activated and sensory systems can be further enhanced to provide intelligent solutions for managing dementia related wandering. For example, we can integrate face recognition features to the existing system [63] to distinguish wanderers from caregivers. In general, both systems address 3 items of eloping behavior in the WHAT domain: wanderer runs off; wanderer enters unauthorized area; wanderer attempts to leave authorized area.

3.2 Systems to track and locate PWD

Tracking systems aim to provide the position of a wanderer at any moment and can be used to locate PWD at risk of wandering. Unlike those in Section 3.4, these systems are invasive and require PWD to wear a tag or transmitter shaped like a watch, pager, or ankle bracelet. The wanderers are then located by radio frequency (RF) range finding, floor sensors or global positioning systems (GPS). RF systems and floor sensors are mainly for indoor monitoring whereas GPS works well outdoors only. We discuss all tracking systems.

3.2.1 GPS Tracking with Mobile Locator Devices

Digital Angel, Inc. [64] has developed a commercial system which employs a GPS-enabled phone to establish a perimeter (termed a “geo-fence”) around the home. Wanderers wearing the phone, who cross

the geo-fence, automatically reveal their position to their caregivers through a server-based notification system of e-mail, pager, and automated telephone calls using synthesized voices. Caregivers can locate the missing wanderer within an accuracy of 30m, and coverage is dependent on cellular telephone service and GPS satellite availability.

Other well-established research works in this category share similar working mechanism with Digital Angel, i.e. combining GPS technology and mobile telephones. These works differ from one another in the proliferation of mobile phone technologies and the systems' localization accuracy. In particular, before the advent of GPS-enabled smartphones, the earliest systems used separate GPS receiver [65] and personal handy-phone system [66] to detect a person's location within 200m and 60m location error (distance between the actual and the located location) respectively. The more recent ones harnessed PDAs to locate missing persons to an accuracy of approximately 10m [35]. These were controlled studies (subjects were instructed where and how to move) with no involvement of PWD.

In other uncontrolled studies (subjects were free to move around), Miskelly [67] first tagged 4 nursing home PWD each with an electronic bracelet that buzzed a pager if the resident wandered into off-limit areas. In the second study [25], he attached GPS-integrated mobile phones to 11 dementia subjects to enable relatives or caregivers to locate them within 5m, except inside buildings or on public transport. Data and evaluation were recorded over a 6-month period. Two important results were found. First, three different types of episodes (wandering outside, wandering into a risk area, removal of a bracelet) were immediately detected by the system and the affected resident was promptly attended to [67]. Second, tracking was accurate when the users complied with wearing the phone. 90% of the location requests exactly matched the information given by the relative/caregiver. Of the location requests that were deemed failures, 95% were due to non-compliance (i.e. not wearing the phone) [25]. In short, GPS-enabled phones are effective in monitoring and locating PWD who exhibit symptoms of wandering.

3.2.2 *RFID Tracking*

In recent years, RFID technologies have been increasingly applied to manage wandering in institutional care settings because of three reasons. Firstly, each RFID device has a unique identification number to distinguish the subjects. Secondly, it can provide compact and real-time information on the person's location, accurate to a few tens of centimeters [31]. Thirdly, a variant of RFID called Ultra Wideband (UWB) offers advantages over passive RFID with its capability to reveal the identity and precise locations (and time) of multiple subjects moving simultaneously [31]. Therefore, it can minimize and probably remove the burden of observation on the subjects especially during night hours.

Several RFID systems have been developed and implemented in institutional care settings. The earliest prototype proposed by Ashida [68] comprised RFID tags, trigger generators, tag receivers and personal computer for data processing. A tag hooked to the subject would send the RF signal when the person is in a trigger field. The tag receiver would receive that RF signal, decode the data, and send the data including date and time, tag ID and trigger ID to a central processing computer. The information was used to monitor the subject's daily behavior. Ashida's system was further enhanced to calculate the distance that the subject moves, display the movement pattern mapping of the subject and the duration of stay at each location [69, 70].

Almudevar [71] instrumented the home of a person at risk for dementia with various RF sensors to reconstruct his or her movement trajectory within the home. Analysis of a 3-week longitudinal data suggested that the methodology was reliable enough to construct the travel trajectory of the person. Regions of high visiting frequency were identified and transitions between the regions were accurately tracked. Further replication is necessary in the homes of more subjects.

Kearns [31] introduced the use of UWB as an advanced method to track a moving transmitter (or tagged PWD) in real-time. It is similar to RFID monitoring systems but has certain advantages. UWB devices

operate at lower power levels and can transmit data over periods of years without battery replacement. The large bandwidth available to UWB-RFID allows potentially very high data transmission rate (to the order of 1 Gbps) over very short range (less than 1m). It is capable of estimating a location accurate to 20 cm in real-time. Trial tests [72] concluded that the UWB-RFID technology is sufficiently reliable and precise to allow accurate measurement of lingering and shadowing behavior. However, UWB systems are costly and they must be precisely calibrated to ensure accurate localization.

3.2.3 *Floor sensors*

Floor sensors such as piezo-electric sensors, piezo-resistors, load cells, or capacitive sensors [129-132] have also been used for indoor localisation and tracking. These sensors are mounted on the floor to collect the pressure profile over footsteps which is subsequently employed to extract ground reaction force features for human identification and tracking.

Compared to other wearable sensors and RFID technology, floor sensors have the advantages of being less intrusive for indoor localisation and having high localisation accuracy. The mean localization accuracy was reported as 0.12-0.5m [133-134]. Accuracy can be further enhanced by increasing the number of sensors per floor unit area. However, high sensor distribution may have negative impact on overall system cost, hardware/software complexity, system scalability and maintainability.

Nonetheless, floor sensors have difficulty in identifying and tracking multiple persons walking at the same time. A previous study reported that the system performed poorly in disambiguating between people when they were separated by 0.5m or less [134]. In addition, the system cannot differentiate persons who have very similar body weights [135]. Generally, the pressure information alone is not sufficient. Hence, additional features and sensors should be combined in a multi-modal perspective to improve their ability in tracking multiple persons on sensing floors [130].

In the healthcare domain, various sensing floors such as Capfloor [136], SensFloor [137], FloorInMotion [138] are commercially available and they have been applied in studies on gait analysis and activity recognition. Cantoral-Ceballos et al. [139] employed an intelligent carpet system – GAITRite, which is based on photonic guided-path tomography in order to capture footstep imaging and display the position and footfall of a person walking on the carpet in real time. The authors plan to integrate the developed technology with other sensing techniques to provide a more holistic picture of activity and rest patterns. Daher et al. [140] used smart tiles and accelerometers to detect falls in elderly people and to recognize daily activities including walking, standing up, sitting, lying down. The recognition sensitivity for each activity is more than 90%. Recently, Huang et al. [141] implemented a trial smart living platform using motion sensing floors that aimed to tele-monitor walking trajectory, mobility level and fall events of older adults. Initial results reported users' keen interest in having the solution installed in larger floor space.

In short, floor sensors are advantageous for indoor localisation in terms of privacy and accuracy. They are non-obstructive and able to identify a person's location with a mean localization accuracy of 0.12m. However, the ability to track multiple people is difficult using only floor sensors. Though using floor sensors in gait analysis and activity recognition studies show promising results, future work and further development need to be done to explore the ability of the technology to detect wandering behavior of PWD.

To sum up, GPS, RF, and floor sensors based tracking systems are able to track and locate PWD in outdoor and indoor settings with high accuracy (5-10m for GPS, 30cm for RF-UWB, 12-50cm for floor sensors). The technologies are mature and commercially available. They provide effective tools to address the WHERE and WHEN domains. Future research can make use of these available technologies and products to study and address more complex aspects of wandering.

3.3 Information services to assist caregivers

Information services are complementary networks of hardware and software that caregivers and organizations use to collect, process, and distribute data regarding PWD who wander so as to provide interventions and improve quality of care.

Lin's another study [34] attempted to build an information platform for care organizations. An eXtensible-Markup-Language-based dementia assessment system combining program code and assessment content was developed to provide caregivers with better flexibility and real-time response ability. With regard to dementia assessment service procedures, care personnel could obtain information concerning a dementia patient's symptoms from family members, enabling them to use the assessment system to analyze the severity of the dementia. This system facilitated the establishment of long-term case files and recording cases' structured clinical dementia ratings (SCDR), mini-mental state examination (MMSE), and daily moods. It then helped to identify easily irritable patients in order to provide additional care mechanisms.

Alzimio [73] is a mobile application that provides activity-based alarms to caregivers of PWD. The activities include staying still, walking, being on bicycle, being in a vehicle, titling, and unknown. The application requires caregivers to designate certain activities as dangerous and an alert message will be triggered and sent to the caregivers when dangerous activities are detected.

Moreno, Hernando, Gomez [74] described a location-awareness service enabler to support and manage wandering-prone activities of a person with mild cognitive impairment. Through an Internet Protocol multimedia subsystem architecture, information about the elderly person's security areas is entered in the user profile. The interface design allows personalization of services depending on user's context and specific conditions or preferences. From the user's location, the service enabler will alert the user's contacts if hazardous situation, e.g. wandering out of the zone, is detected.

WanderHelp [75] is a client-web service designed for standard mobile phones. It incorporates a number of services that allow caregivers to define zones (safe zone, dangerous zone, amber zone) and alarm-raising protocols. It also permits the caregiver to track a PWD but only when an alarm has been generated and the PWD fails to respond. 52 users were recruited to use the system and they were reasonably satisfied with the service it offers. However, only 23% of users had actual experience of caring for a PWD and not all of these PWD had experience of a wandering episode. Therefore, the authors suggested to replicate the study with a group of caregivers who have experienced with PWD who wander so as to garner new insights on the system's potential use in practice.

In brief, information systems directly assisting caregivers in monitoring and managing wanderers are scarce. Future works should focus more on characterizing the HOW domain of wandering and providing assistive tools to caregivers. For example, we can document behavioral techniques to intervene wandering and implement a mobile application to teach and guide caregivers to apply such intervention techniques when PWD wander.

3.4 Tools to measure frequency, repetitiveness, temporal distribution

There have been tools that capture 2 dimensions of wandering: frequency and temporal distribution. Frequency was measured as the rate of wandering episodes per hour. Temporal distribution was measured in different forms: walking time duration, time spent on wandering, temporal variability of wandering locomotion, duration of wandering episodes. These dimensions were used to correlate wandering and cognitive performance.

Hayes and colleagues [17-18] measured the walking time duration of 14 elderly seniors living in their own homes. Three passive infrared sensors were placed on a path in the home identified as the longest path along which the subject typically walked continuously from end-to-end. These sensors were triggered as a person walked past the monitored path. In each observation period, if the sensors are s1, s2, and s3,

then each time the sensors fired in the order (s1, s2, s3) or (s3, s2, s1) without another intervening sensor firing, the subject was considered to have walked along the monitored path and the time difference in firing events was calculated as the observed sample of the walking time. Kernel density estimation was then used to approximate the distribution of walking time. They found that variability in walking time was greater among the 7 participants with mild cognitive impairment than those 7 without.

Biomechanical devices including Actillum, StepWatch, and TriTrac-R3D were used to estimate the time spent on wandering of PWD [76]. The proportion of time during which motion was detected by each device was compared to the proportion of time during which wandering was observed by human observers. StepWatch produced the closest estimate of time spent wandering (16.8%) compared to 15.4% assessed by human observers. Actillum and TriTrac-R3D detected much higher percentages, 63% and 49% respectively, reflecting oversensitivity to movement that is not wandering behavior.

Makimoto et al. [77] employed RFID tagging systems [69-70] to record locomotion data which were then used to measure temporal variability of wandering locomotion. Two indicators were calculated: the percentage of hours with locomotion and the median distance traveled per hour. They found that the former indicator was negatively correlated with the subject's cognitive ability, which did not correlate with the latter indicator. This suggests that cognitive impairment may be better reflected by the frequency of wandering rather than the total distance travelled.

Algaie and associates [78] videotaped wanderers in long-term care settings. They used Noldus Observer 5.0 software and human observers to code videotapes and measure the rate and duration of wandering episodes. They found that MMSE scores were negatively correlated with overall duration of wandering and were not significantly correlated with rate-related parameters.

In conclusion, current tools and software are able to capture the frequency and temporal distribution dimensions in the WHAT domain of wandering. There is no automated tool to capture the repetitiveness

dimension (i.e. wanderer goes repeatedly to the same location using the same route while traveling indoors). We suggest using camera video or RFID-UWB systems to capture the locomotion of wanderers and determine its repetitiveness by applying computational algorithms and machine learning techniques.

3.5 Tools to recognize wandering patterns, spatial disorientation

There are previous studies that capture geographical patterns of wandering. In addition, there exist systems that measure one specific aspect of spatial disorientation, i.e. getting lost.

3.5.1.1 Recognize Wandering Patterns

Nakaoka et al. [79] quantitatively described locomotion in PWD in terms of distance moved per day, and pacing and lapping movements. Spearman correlation coefficients were obtained to examine the relationships between spatial disorientation and relevant variables such as cognitive function and age. They found that repetitive pacing and lapping movements were observed in participants with fronto-temporal dementia. Therefore, routinized pacing is one of the predictors for fronto-temporal dementia and pathological changes in the brain could account for this behavior. However, they pointed out that the major limitation was to measure random movements and quantify pacing or lapping patterns.

Another study also tried to detect wandering locomotion including lapping and pacing patterns based on user's GPS trajectory [93]. A data-driven method is proposed to examine and count turning points in an ongoing trajectory. The angular sum of these points serves as the basis to distinguish lapping and pacing movements.

In a later work, Kearns et al [80] found that fractal dimension (a measure of randomness in 14 ALF residents' movement paths continuously recorded over 30 days using UWB-RFID sensors) was significantly higher in persons with lower MMSE scores signifying cognitive impairment. The fractal dimension is computed by comparing the measurement of a line or surface at multiple scales. A truly straight line has a fractal dimension of 1, while a line that crosses a plane enough times to completely cover the surface

(i.e. follows a Brownian motion) has a fractal dimension of 2. Thus when describing the fractal dimension of a line, $1 \leq \text{Fractal Dimension} \leq 2$ [81]. It can also be applied to the 3D analysis of surfaces such that the fractal dimension ranges from 2 to 3. Fractal dimension in Kearns' studies was computed based on the 2D geographical travel paths recorded by Ubisense location systems [82]. In addition, fractal dimension is able to measure spatial variability of ambulation of multiple individuals simultaneously over extended periods [83].

In a subsequent study of 28 subjects [84] recorded over one month replicated the findings of Kearns [68] and found that the randomness of the paths taken by elderly ALF residents reliably differentiated PWD from those without the disorder. Most recently Kearns et al. [85] determined that randomness in the paths of 53 ALF residents' walking patterns recorded over a period of 1 year was strongly related to their imminent fall risk, establishing an important relationship between the random movement patterns in older persons and the risk of falling.

3.5.2 Detect Spatial Disorientation

Lin et al [33] proposed a framework that combines RFID, GPS, Global System for Mobile, and Geographic Information System (GIS) to construct a stray prevention system. It provides four monitoring schemes: indoor residence monitoring, outdoor activity area monitoring, emergency rescue, and remote monitoring. The service platform assists in identifying the real-time positions of missing elderly using Internet-connected devices. Chang [58] implemented a mobile location-based networking system for a specific group of subjects: people with mental illness who travel to and from work. The system was created to assist both the subjects and their job coaches. The job coaches work with the subjects to support them in learning new jobs, and more importantly remaining socially connected. The subjects may at times still require assistance to decrease the risk of getting lost. The PDA attached to the subjects reports their current location to a server through GPRS connectivity. The server tracks the subject who deviates from the pre-set route to or from the workplace, and then the matching module locates the job coaches who

are within a certain distance from the lost subject. The system also includes a HELP button on the PDA that the user can press to ask for help while travelling. Based on this initial work, Chang and Wang [86] recruited 8 subjects to test the system's ability in identifying the job coaches within a distance from the target user when the subject pressed the HELP button. The experimental results showed that the precision ranges from 89 to 100% and the recall from 94 to 100% for all subjects. Precision is the proportion of relevant job coaches among all those identified by the system (which may include irrelevant ones). Recall is the proportion identified by the system among all relevant job coaches (some of which not identified by the system).

Batista, Borrás, Casino, and Solanas [87-88] proposed techniques to detect cycles, orientation, direction changes that could be used to detect wandering. The group could not detect wandering patterns in human trajectories that they collected; however, they found that there are significant and detectable differences between normal and wandering trajectories. In the wandering trajectories, the path contains few locations where the person frequently visits than the path of normal walking.

In summary, current technologies to capture wandering patterns and spatial disorientation are still at early stage. One challenge lies in the polymorphism of patterns (e.g. lapping in the same or opposite directions) and forms of disorientation (e.g. wanderer cannot locate the dining room or his or her own room). The lack of ground truth and benchmark datasets also makes it difficult to evaluate and validate the algorithms.

3.6 Applications that analyze proximal factors to detect wandering

Several applications address the WHY domain of dementia-related wandering. These applications analyze proximal factors to detect the risk of wandering in PWD.

Opportunity Knocks [26] and iRoute [89] use GPS-enabled phones to learn the individual's standard travel routes in outdoor environments. Patterson, et al. [26] (Opportunity Knocks) have proposed a hierarchical

Dynamic Bayesian Network model, an extended Bayesian Networks, which is able to infer common destinations such as frequently used bus stops and parking lots that users visit. It then estimates the transition probability matrices between these destinations, “trip segments and streets” and subsequently calculates the most likely trajectories. To detect abnormal events such as wandering, the approach uses two models with different transition parameters. “The first one assumes the user is behaving according to his personal historical trends and uses the learned hierarchical model for tracking. The second tracker assumes a background model of activities and uses an untrained prior model that accounts for general physical constraints but is not adjusted to the user’s past routines. The trackers are run in parallel, and the probability of each model given the observations is calculated. When the user is following his ordinary routine the learned hierarchical model should have a higher probability, but when the user does something unexpected the second model should become more likely” [26].

iRoute [89] has the same objective and approach with Opportunity Knocks. However, their inference system uses the agent approach with the Belief-Desire-Intention (BDI) architecture [90]. The route prediction and matching is based on user preferences and the learned routes information stored in the BDI agent’s belief base. The agent tracks the user towards the predicted route or routes until the user reaches one of the predicted destinations. However, users can have more than one predicted route at a certain time of the journey. During the travel, if the user walks off the route, then the agent tries to guide the user (using voice-activated navigation) back to the last predicted route. If the user continues moving in the wrong path, then the agent will notify either the care staff or the relatives.

iWander [91] proposes a Bayesian multi-variant model to detect the subject’s probability of wandering. The variables or proximal factors include the person’s standard travel routes and others like age, severity of dementia, time of the day, current weather conditions and total time spent outside. They argue that time of day greatly impacts wandering because about half of dementia patients experience night time walking of which a significant number result in the patient getting lost. Dementia patients are outside less

during night hours and during bad weather. So, time of the day and weather conditions also affect the probability of wandering. Also, older adults who have more severe dementia and suffer from more advanced stage of dementia are more susceptible to wandering. Analyzing these variables against a collection of existing data can help classify behavior as normal or abnormal (wandering or not wandering). Their learning approach consists of two phases. First, the data is passed through a one class support vector machine. This filters out obvious, normal activities. After that, data is passed to a nonlinear regression function which will classify a behavior as normal or abnormal.

Similar to iWander, LaCaSa [92] also used GPS trajectories and proximal factors known as home location, close-to-home locations, and far-from-home locations to estimate the risk of wandering faced by PWD. Different with iWander, LaCaSa employed a partially observable Markov decision process for reasoning. In addition, the application also activates the appropriate response when wandering occurs, such as prompting the PWD or calling the caregiver.

A recent medical study [94] measured the emotion expression of PWD (facial displays, vocalizations, and body movement/posture) as affective factors to predict wandering behavior. They used hierarchical linear modeling and Poisson regressions to explore the relationship of observable emotional expression and wandering. Their results revealed that positive emotional expression was associated with a 1.03 (confident interval: 1.02-1.04) increase in wandering rate, and negative emotional expression was associated with a 0.11 (confident interval: 0.83-0.95) decrease in wandering rate, even after controlling for cognitive function and subject's characteristics such as age, sex, race, and education.

In short, most of the above applications used location trajectories as proximal factors to detect wandering. The principle is daily mobility or travel behavior tends to be repetitive and follows a recurring pattern. Therefore, disoriented wandering can be detected by looking for trajectories that are not usual or optimal. We realize that detecting wandering by using proximal factors is a long-term goal, which

requires the combinations of advanced sensing technology, accurate recognition algorithms, and efficient machine learning algorithms.

3.7 Applications to study background factors

These are longitudinal studies which use wandering as a feature or predictor to study background factors such as neurocognitive factors or health status.

Hsiao [95] deployed a wireless sensor network system in the university hospital's elder care center for 8 months. They collected location traces and investigated the daily and long-term mobility of 4 volunteering elders. They found a recurring pattern in each elder's daily mobility. The pattern, however, differed from individual to individual. These suggested that merely quantifying how much the elders move around the facility will not be sufficient for behavioral modeling. Exact location of the elders' presence, rather, is more relevant. They concluded that long-term location tracking, not just the mere quantity of mobility, allows discovery of the moving patterns and in turn makes early detection of the elders' physical or mental problems possible.

A dataset of indoor locations recorded from 6 PWD during a year (about 900 individual daily traces organized in groups of 14 days) was used to assess the state of dementia in a real-world nursing home. By applying k-Nearest Neighbor classifier, the authors [96] were highly accurate (92%) in classifying a patient's state of well-being as positive or negative. The ground truths (positive and negative states) were documented by the attending nurses. Their results once again support the idea of using motion analysis to manage wandering behavior and well-being of PWD.

A clinical study [97] used duration, rate, general health, cognitive impairment, circadian rhythm, age, and sex factors to differentiate three types of wanderers (classic, moderate, and subclinical). They applied principal component analysis and clustering techniques on the multi-dimensional dataset of 142 PWD. They found that duration and rate parameters primarily distinguished the 3 types of wanderers. Cognitive

impairment, upper and lower gastrointestinal tracts differed between groups of wanderers and from non-wanderers. Measures of circadian rhythm, age, and sex did not differentiate types.

Briefly, while there are initial efforts to study background factors that affect wandering and vice versa, the long-term effects and significant results from such studies have not been seen or achieved.

3.8 Discussion

3.8.1 Issues

Several issues need to be considered when developing assistive applications and systems for managing dementia-related wandering.

3.8.2 Design issues and human factors

Assistive applications for managing wandering aim to benefit the wanderers, the caregivers, and the clinicians/researchers. Designing applications for these stakeholders requires special attention to training and support [98].

For wanderers with dementia, due to their cognitive, perceptual, and physical limitations, such applications should not rely on their efforts. The wandering applications should be installed when the person is at the early stages of dementia. A previous study [99] observed that people with mild stage memory impairment were able to use and benefit from the GPS tracking technology to live more independently. They were able to move with greater freedom and security when using GPS systems, and some were also able to take care of the devices by themselves. Persons with later stage memory impairment could not learn to adopt the technology as it was too complex for them.

When deploying or selecting sensors for wanderers with dementia, we need to consider the following factors.

- **Size.** The size of a sensor is important. In general, a smaller size is more acceptable to the user. Small and lightweight sensors are easy to attach to the body, less intrusive, and more convenient to use.
- **Power consumption.** Most sensors are powered by batteries. With lower sensor energy consumption, the battery can last longer – ideally, over the sensor’s lifetime. Some sensors can harvest power themselves; however, there may be maintenance problems. Short-range wireless energy submission can be used also. However, the frequency and difficulty of related maintenance tasks such as charging and cleaning should be minimal.
- **Mobility.** Sensors should be able to communicate with other sensors or control devices while in motion, as they are often attached to a mobile user. There should be minimal physical interference between sensors and movement. Any potential difficulties in attaching a sensor or removing it should be eliminated.
- **Processing capability.** A sensor that performs some simple data processing (e.g. filtering or removing additive noise) before sending useful data to a data collector can help to reduce redundant data transmission.
- **Storage capability.** A sensor may possess a small amount of local storage for critical (or preprocessed) data prior to transmission. This improves robustness when the data communication channel becomes temporarily unavailable or interrupted.

Sensor radiation and compatibility with human body tissue must also be taken into account as longtime exposure to radiation from wireless devices can raise concerns about possible health hazards. Other factors may include clinical approval, durability, and accuracy of measurement, social and fashion concerns. For example, using sensors embedded in a smart phone or wearing sensors that appear as shirt buttons can help avoid unwanted attention and possible stigmatization [56].

Important factors of wandering management applications targeting caregivers, researchers and/or clinicians are interface design and functionality. Interfaces of assistive applications tailored for caregivers

should be kept as simple as possible. Some details such as large button size, quick response of touch screen, not too many steps/options to choose from, easy navigation, and nice use of pictures or metaphors, good use of colors are preferable [100]. In addition, the applications must take least time and minimal effort to learn and familiarize because caregivers already have to juggle many tasks to take care of PWD. Applications for researchers and clinicians should be adaptive to the context and their specific needs, e.g. measuring wandering dimensions, so as to maximize the usability of the applications.

3.8.3 Ethical, privacy, and security issues

PWD and/or their family members must be well-informed of possible consequences of assistive applications to protect their rights. In particular, there is an ethical and practical concern to the tagged person, i.e. the person's liberty is limited. For moderate and severe dementia patients, electronic tagging arguably satisfies an ethical principle and decreases stigma. Being lost and half dressed in the middle of the night near a dual carriageway is hugely stigmatizing, and electronic tagging may avoid this [101].

Privacy of users must be safeguarded and the involved parties should ensure confidentiality when personal data are collected [102]. Surprisingly, most nursing home residents do not share those views. When the moderator brought up the privacy issue to groups of nursing home residents, it was quickly dismissed as secondary. Residents are more concerned with the weight of tracking device placed on them, i.e. "a device should weigh no more than 113g if attached to an arm or leg, but it could weigh 227g if the device was worn on a belt" [57]. Nursing staff also support electronic monitoring of PWD because it enables them to provide better quality care and encourages PWD to live more independent lives.

While the prospective value of assistive applications far outweighs privacy concerns [57], systems should be designed with good built-in security features. It has to guard against scenarios that might lead to serious security breaches. For instance, intruders might obtain information about the wanderer's habit of leaving home at a particular hour, and use such information to break into the house, potentially even

endangering the person's life. Therefore, the user's security requirements should be determined before the design stage of the applications and systems [103]. All communications should be secure and encrypted. This is especially important in the case of wireless communications which are easier to intercept [104]. Personal monitoring devices should authenticate the identity of the rightful owner using unobtrusive biometrics or possibly key physiological signs to avoid any data tampering (owner-aware devices [56]). Different levels of access authority should be granted to different users and the relevant data required or collected within the suite of assistive applications is properly managed on a secure and password-protected database [105].

3.8.4 Economy Discussion

Currently, the cost of location systems and devices for managing wandering is high for personal users. Typically, the total cost of an intelligent safety phone with integrated elopement prevention is 950USD (including installation) [99]. A UWB-RFID system with 4 sensors can cost 7000USD in the USA and 16000USD in Asia markets [82]. Devices to monitor activities such as wearable inertial sensors range from 1300USD to 3500USD per item [106]. Though such cost is high for personal users, it is more affordable if group users share the systems and services together. For example, a dementia care centre purchases a system and charges its clients a fee for using the devices with the service. The cost per person will be reduced significantly. A previous study reported that the typical rental cost of the devices without other services is about 13USD to 65USD per month. These costs are not high in exchange for the following benefits:

- For **patients**, as a diagnostic sign for preclinical dementia, timely recognition of wandering provides an opportunity for early treatment of dementia and delay nursing home entry. This will realize significant cost savings because once transferred into formal care, the annual cost of care for a patient exceeds USD 32,000 in high income countries [12]. In addition, the quality of care for PWD prone to wandering will be improved. In fact, the identification of specific types of wandering helps point to

possible causes or reasons for wandering. If he/she changes from a non-wanderer to a wanderer, it may reflect either advancing dementia or some undiagnosed medical event that affects cognition, perhaps causing a delirium.

- For **caregivers**, wandering management technology will help them cut down time spent on surveillance of wandering behavior. Researchers and clinicians who harness the technology are able to garner new knowledge on the antecedents and consequences of risky wandering. This knowledge can critically enable health professionals to individualize interventions and effective approaches tailored to different types of dementia and patients.
- For **societies**, long-term research outcomes will reduce the cost of care and use of public funds for institutional care. If technologies can help a caregiver spend 1 hour less per day to look after a dementia wanderer, the world will annually save USD 155 billion in 2014 dollars. To governments and agencies concerned with the well-being of elderly population, particularly those who have dementia, this represents a methodological breakthrough worthy of significant investigation.

3.9 Conclusions and future directions

3.9.1 Conclusions

Table 3.1 summarizes the reviewed works and highlight what has been addressed and what has not been achieved. Technologies to geo-fence and prevent elopement, track and locate wanderers are mature and stable. The availability of commercial products and various tracking applications on mobile platforms is clear evidence. On the other hand, information and communication services that assist caregivers are scarce. Current assistive tools do not support comprehensive measurement of a variety of wandering dimensions. Typically each of them is built to quantify a single, though possibly different dimension of wandering locomotion. There is still a need to provide additional assistive support and integrate these tools together. Automated technologies to recognize wandering patterns and spatial disorientation, analyze proximal factors, as well as realize negative outcomes and study background factors are limited.

These technologies are still at the early stage and not many of them have been validated in large scale or longitudinal studies involving PWD from diverse geographical regions and medical backgrounds. Based on these observations, we would like to suggest future research directions in both the short- and long-term. We discuss the issues and problems when developing assistive applications for managing wandering.

Table 3.1: Summary of reviewed works

Domain	Category of works	What has been addressed	What has not been addressed
WHAT	Tools to measure frequency, repetitiveness, temporal distribution	Measure frequency: rate of wandering episodes per hour [78] Measure temporal distribution: walking time [19,20], wandering time [76], temporal variability [77], duration of wandering episodes [78]	- Automated tools to document and incorporate all dimensions of wandering - Tools or applications to measure repetitiveness: go repeatedly to the same location, travel repeatedly the same route while walking indoors
	Tools to recognize wandering patterns and spatial disorientation	Classify pacing, lapping, random patterns [79,80,84,93] Recognize an aspect of disorientation: getting lost [33,63,86]	- Algorithms to address the variance in temporal, spatial, and geometrical shapes of patterns within the same wanderer, across different wanderers, between wanderers and non-wanderers - Algorithms to address other types of disorientations: wanderers cannot locate dining room/own room/bathroom without help; wanderers bump into obstacles or other people while walking alone or walk about aimlessly
	Tools to prevent elopement	Wanderer runs off, attempts to leave authorized area [49,57,58] Wanderer enters unauthorized area [59,60,61,62]	(Mature technologies)
	Negative outcomes	Falls [85]	Fatigue, inadequate food intake, injuries
WHERE WHEN	Track and locate PWD	GPS tracking [25,35,65,66,67,64] RFID and/or UWB tracking [31,69,70,71] Floor sensors [129,130,131,132,133,134,135]	(GPS tracking, RFID and/or UWB tracking are mature technologies) The ability to track multiple people concurrently walking on the floor

HOW	Information services	Dementia assessment [34]	Tools that provide intervention cues (environmental modification, behavioral techniques) to instruct caregivers
WHY	Tools that analyze proximal factors to detect wandering	Physical environment, e.g. deviation in location trajectories [26,89,91,92,93] Affective states, e.g. emotional expression [94]	Other factors that could trigger wandering including: - Physiological need states, e.g. hunger, agitation - Affective states, e.g. boredom or loneliness - Physical and social environment, e.g. ambient conditions
	Applications to study background factors	Health status, e.g. well-being [95,96] Socio-demographics, e.g. age, sex [97]	The relationship of wandering and background factors such as: - Neurocognitive factors, e.g. visual-spatial memory - Health status and socio-demographics, e.g. pain, constipation, education, previous jobs

3.9.2 Short-term Research Work

Assistive information services: For example, assistive applications to provide recommended behavioral and environmental modification techniques for caregivers to target different wandering scenarios. Such applications can also contain videos, images, and scenarios showcasing different wandering behaviors of PWD. Direct caregivers can then learn to recognize wandering and provide immediate interventions. These applications will serve as educational or training tools for caregivers who have limited knowledge of wandering and its associated outcomes.

Measurements of frequency, repetitiveness, temporal distribution of wandering: Automated tools are needed to measure these 3 dimensions. So far, there are attempts to automatically measure frequency and temporal distribution but not repetitiveness. Thus, future assistive applications can consider using locomotion data to identify repeated locations or routes traveled by wanderers. Integrated applications to automatically measure these 3 dimensions are essential to characterize dementia-related wandering.

3.9.3 Long-term Research Work

Recognize wandering patterns and spatial disorientation: The core research concept on wandering aims to quantify random movement, which has been a difficult task for human observers to master. Most current algorithms to recognize wandering patterns and spatial disorientation need to improve in reliability, robustness and accuracy. The challenges lie in the polymorphism of patterns and forms of disorientation, their differences in spatial, temporal, and patterns' geometrical shapes from wanderers to wanderers, from wanderers to non-wanderers, and within a wanderer. In addition, the unavailability of ground truth labeled data as well as standard benchmark datasets make it very difficult to evaluate and validate the algorithms. Appropriate visualization tools can also be designed to enable researchers and clinicians to easily view these wandering dimensions of PWD, for example on a computer monitor with an intuitive user interface.

Analyze proximal factors to detect wandering: In general, such systems and assistive applications require 3 subsystems. Firstly, context-aware sensing subsystems are needed to recognize relevant proximal factors. Secondly, automated algorithms to continuously monitor and detect changes in proximal factors are required. Thirdly, probabilistic models and regressions are applied to estimate the likelihood of wandering. Combinations of advanced sensing technology, accurate recognition algorithms, and efficient machine learning algorithms are potential to accomplishing this goal.

Realize negative outcomes and study background factors: Longitudinal studies can be conducted to achieve these long-term goals. An example of such studies is we can monitor wandering and its progress to early detect deterioration in visual-spatial memory and cognition of PWD. Tools to characterize full spectrum and dimensions of wandering as well as background and proximal factors are instrumental in conducting such studies and developing the technologies. Synergistic collaboration between technologists, gerontologists, caregivers and PWD is necessary to ensure the feasibility of adoption of such technologies in healthcare settings.

Chapter 4 Wandering Patterns Classification Using Spatial Temporal Information

This chapter includes five sections. Section 4.1 introduces the Martino-Saltzman (MS) model of wandering patterns. Section 4.2 discusses the dataset used in our study. Section 4.3 produces the results of using classical machine learning approach to classify wandering patterns of people with various stages of dementia. Section 4.4 presents the tree-based algorithm we create to classify wandering patterns. Section 4.5 demonstrates a working prototype of the algorithm on a mobile phone.

4.1 Martino-Saltzman (MS) model of wandering patterns

Martino-Saltzman [107] systematically evaluated the travel patterns of 40 nursing home residents with dementia, 24 of whom were identified by nursing staff as wanderers or suspected wanderers. The remaining 16 residents were non-wanderers. Travel was monitored continuously for 30 days and four basic travel patterns were observed: direct travel, lapping, random travel, and pacing. Travel efficiency (percentage of direct travel) was significantly related to cognitive status, with inefficient travel most prevalent in severely demented participants. The findings have facilitated further research in geriatrics and have been used in various dementia-related studies. First, inefficient travel (or wandering) patterns including lapping, pacing and random were operationally used to define wandering behavior of PWD. Second, wandering patterns combined with other spatial and temporal parameters can identify different types of wanderers and provide useful information on the wanderer's cognitive performance [97]. Third, detailed findings from several medical studies [23, 37, 108-110] lent evidence to the correlation of wandering patterns and cognitive performance. Random-pattern wandering is considered the most serious symptom in PWD, followed by lapping and pacing. Increasing amounts of random-pattern wandering reflect higher degree of global (bilateral) hippocampal damage in humans and serve as a potential marker for dementia progression [23]. Frequent lapping signifies a deteriorating ability to way-

finding in PWD and can be used as a predictor for unilateral hippocampal damage [37, 108]. Pacing is not associated with levels of cognitive impairment, but is more indicative of agitation and anxiety [109-110]. Direct patterns are efficient but their character changes might also indicate cognitive deficits.

Figure 4.1: Travel patterns of nursing home wanderers. The plan view of a room is represented by a rectangle. Smaller rectangles represent different parts of the room and the dash lines show the travel paths.

To the best of our knowledge, we are the first group aiming to detect wandering patterns of PWD based on MS model. Here, we present a typology of wandering. We will first define three concepts: location, movement, and episode. A **location** may be represented in terms of 3-D space coordinates or broad regions (e.g. kitchen, dining room, etc.). A **movement** is defined as moving from the present location to the next immediate location. Each **travel episode**, be it wandering or non-wandering, consists of one or more consecutive movements. Each episode has a start location and a stop location.

For convenience, we denote L_1 , L_2 , L_3 , and L_4 as locations. Martino-Saltzman et al. [107] observed the spatial movements of both wanderers and non-wanderers with dementia and identified four patterns of independent travel in wandering subjects (Fig. 4.1):

1) *direct* – a single straightforward path from one location to another without diversion. An episode comprising two or more consecutive direct paths to different locations is also considered as direct. A travel path that passes through the same location twice or more is not considered direct because one of the sub-trajectories is redundant. For example, a direct path from L_1 to L_4 includes passing through L_2 and L_3 . Thus an episode involving $L_1L_2L_3L_4$ is direct. If an episode takes the path $L_1L_2L_3L_1L_2L_3L_4$, the first sub-path from L_1 to L_3 and back to L_1 is considered redundant and inefficient. Therefore, direct pattern would comprise single straightforward path or a path that moves through different locations. An episode with the path $L_1L_2L_1$ is direct.

2) *pacing* – a repeated path back and forth between two locations. We specify that a pacing pattern would include more than two (at least three) consecutive to-and-fro movements. For example, the path $L_1L_2L_1L_2$ is classified as pacing since it has three repetitive movements: L_1 to L_2 , L_2 back to L_1 , and L_1 to L_2 again.

3) *lapping* – a repeated circular path involving at least three locations [97]. A lapping pattern would contain at least two repeated circular routes involving at least three different locations, either in the same or opposite direction. For instance, the paths $L_1L_2L_3L_1L_4L_1L_2L_3L_1$ (same direction) and $L_1L_2L_3L_4L_3L_2L_1$ (opposite direction) are considered as lapping;

4) *random* – a continuous path with multiple locations in no particular order. A random pattern must not be a direct pattern and contain at least one location which is repeated at least twice. Due to these two conditions, lapping and pacing patterns are subsets of random patterns.

With respect to distance traveled and time taken, direct pattern is efficient travel and is not regarded as wandering [110]. The other three patterns (random, lapping, and pacing) are inefficient and they constitute different types of wandering.

4.2 Dataset

4.2.1 Subjects' characteristics

Movement datasets of five nursing home residents with different stages of dementia are used in our study. The demographic characteristics of the subjects are reproduced in Table 4.1. All five subjects [69-70] were diagnosed with dementia (through the Mini-mental state examination) and could walk independently [70].

Table 4.1: Characteristics of the subjects [69-70]

Variables	n = 5	
	Percentage (%)	Mean $\pm$ SD
Age (years)		72.4 $\pm$ 8.4
Sex		
Male	40.0	
Female	60.0	
Diagnosis		
Alzheimer's Disease	60.0	
Vascular Dementia	40.0	

4.2.2 Subjects' movement data

The movement data were collected by Makimoto et al. [69-70]. Active RFID activity monitoring systems (Power Tag, Matrix Co. 6-1-2 Nishi Tenma, Kita-ku, Osaka, 530-0047 Japan) were installed at two dementia care units in Japan and Korea. Antennas were set up on the ceilings of all the rooms in the units. Individual RFID tags (measuring 2.8 cm x 4.2 cm x 0.68 cm) were worn by the subjects in the back collar of their shirts. A personal computer system then recorded the movement information including the tag ID, the tag receiver ID, time and date. Each tag receiver ID (or location ID) uniquely identified the room visited by the monitored subject.

The specifications of the Power Tag system [111] are presented in Table 4.2. The system is able to monitor the whereabouts of a subject and the rhythm of daily activities such as walking distance per day and

frequency of toileting. Makimoto et al. [69-70] employed the system to record the room-to-room movements of monitored subjects as they moved within the care units over a 24-hour period.

Table 4.2: Specifications of the Power Tag RFID system

Tag Receiver	
Receiving Frequency	304.2, 309.9, 314.26 MHz
Number of RF Inputs	1
Type of Modulation	Frequency Shift Keying
Signal Input Sensitivity	-90dBm to -30dBm
Data Output	RS232C 9600bps
Power Supply	AC 90/110V 50/60Hz
Trigger Generator	
Output	1 Arms/93.75kHz
Power Supply	DC 12V/2A AC Adapter
RF TAG	
Output Frequency	304.2MHz or 309.9MHz or 314.26MHz
Modulation	FSK 60kHzp-p
RF Output Level	500i V/m at 3m offset (Weak Radio Wave)
Wake up Signal	>100m Vp-p 93.75kHz by Electromagnetic
Signal Rate	93.75kps
Power Supply	DC3.3V ML1220 Rechargeable Battery

The graphical representation of the movements for each subject (labeled as A, B, C, D, and E) is reproduced in the Appendix. Subjects A, B and E were monitored in the same unit in Japan whereas subjects C and D were monitored in another same unit in Korea. We label the semantic locations of the two units by integer numbers for computational purposes (Table 4.3).

Table 4.3: Numerical labels of semantic locations

Care Unit in Japan		Care Unit in Korea	
Locations	Label	Locations	Label
Room 303	1	Room 5304	1
Toilet	2	Toilet 5304	2
Function Hall	3	Activity Room 2	3
Dining	4	Corridor 5301	4
Room 302	5	Corridor Activity Room 2	5
Bathroom	6	Nursing Station	6
Room 301	7	Corridor 5306	7
Room 305	8	Room 5306	8
Emergency exit (ee)	9	Corridor 5309	9
		Activity Room 1	10
		Corridor 5303	11
		Elevator	12
		C	13

4.2.3 *Ground truth estimation*

In total, 120 hours (24hours per subject x 5 subjects) of data were recorded by Makimoto et al. This original movement dataset consists of 1163 instances. Each instance has four attributes: the time, date, tag ID and location ID.

Two steps are needed to establish the ground truth. The first step is to extract every travel episode bounded by its start and stop locations. This is done using an automatic episode segmentation algorithm. The second step is to apply MS model manually to map each episode to one of the four patterns: direct, random, lapping, or pacing.

Step 1: Automatic episode segmentation (Temporal information was used in this step)

To segment an episode, we need to identify its start location and stop location. Ideally, an accelerometer attached to the monitored subject can be used to accurately determine the start/stop locations of each episode. However, even though such motion information is not available in the movement records used in this study, we are able to obtain good estimation of the start/stop locations from the temporal information.

For each subject's dataset, we assumed the location of the first data instance was the start location of the first episode. The start location of any subsequent episode would be the immediate location after the stop location of the previous episode. The stop location of an episode was defined as one where the subject spent more than 15seconds (same as the value used in standard protocol by gerontologists [112]).

Suppose the RIFD system recorded that the subject entered location L_1 at time t_1 and entered the next immediate location L_2 (after being at L_1) at time t_2 ($L_1 \neq L_2$ and $t_1 < t_2$). The total travel time from L_1 to L_2 ($t_2 - t_1$) is bounded by:

$$t_2 - t_1 \leq \mathbf{totalTh} = 15seconds + maximumDirectTravelTime + wanderingOffsetTime$$

- *15seconds* is the stop threshold.
- *maximumDirectTravelTime* is the maximum time to travel directly from L_1 to L_2
- *wanderingOffsetTime* is the time the subject may wander on the direct path between two furthest locations. It is zero if there is no wandering.

Therefore, whether or not L_1 is the stop location of an episode can be easily determined by comparing the total travel time ($t_2 - t_1$) with **totalTh**.

In indoor environments such as dementia care units [69-70], the *maximumDirectTravelTime* is bounded by the ratio of the maximum distance between neighboring locations (rooms) and the minimum walking speed of the subject. The walking speed of a subject can be retrieved from the RFID system. For the current dataset, we used the empirically obtained threshold, **totalTh** = 55seconds (maximum distance = 13m, minimum walking speed = 0.53m/s, and *wanderingOffsetTime* = 15seconds) to do automatic episode segmentation.

We apply the technique described above to all five subjects' datasets. In total, 220 travel episodes were identified (40 ± 30 episodes per subject). Each travel episode consists of a sequence of locations the subject had traveled.

Step 2: Manual classification of an episode's travel pattern (Spatial information was used in this step)

Based on the sequences of locations traveled within an episode, we manually classified the travel patterns of each episode into one of four types: direct, random, lapping, and pacing. We observed the sequence of traveled locations and the contextual information (e.g. meal times, layout of the care unit, the intended destination the subject wanted to travel to) to distinguish between direct and inefficient travels. If it was an inefficient travel, we further checked for pacing, lapping, or random pattern. The pattern of the episode was then concluded accordingly. If there were multiple patterns within an episode, the concluding pattern was the one which had the most number or the most severe one (ascending order of patterns' severity:

pacing, lapping, and random). These manually classified results serve as ground truths for evaluation of the automated algorithms. Descriptive statistics for each type of travel pattern are summarized in Table 4.4. For each type of patterns, the first row shows the total number of episodes identified. The second row represents the range of episode durations. The third row represents the mean and standard deviation of episode durations.

Table 4.4: Ground truth estimation of travel patterns (D: Direct, R: Random, L: Lapping, P: Pacing)

Patterns and Statistics		Subject A	Subject B	Subject C	Subject D	Subject E	All Subjects
D	Number of Episodes	29	22	40	13	22	126
	Range (seconds)	14 – 127	36 – 141	13 – 89	12 – 31	9 – 84	9 – 141
	Mean $\pm$ SD	(39 $\pm$ 37)	(45 $\pm$ 49)	(28 $\pm$ 27)	(18 $\pm$ 8)	(23 $\pm$ 26)	(32 $\pm$ 34)
P	Number of Episodes	2	4	10	1	0	17
	Range (seconds)	135 – 156	61 – 326	26 – 115	66	0	26 – 326
	Mean $\pm$ SD	(146 $\pm$ 15)	(169 $\pm$ 112)	(70 $\pm$ 24)			(102 $\pm$ 69)
L	Number of Episodes	1	5	34	1	5	46
	Range (seconds)	386	182 – 781	70 – 1545	105	102 – 234	70 – 1545
	Mean $\pm$ SD		(423 $\pm$ 223)	(351 $\pm$ 309)		(179 $\pm$ 53)	(335 $\pm$ 282)
R	Number of Episodes	0	5	13	7	6	31
	Range (seconds)	0	256 – 674	87 – 173	70 – 220	130 – 430	70 – 674
	Mean $\pm$ SD		(383 $\pm$ 168)	(126 $\pm$ 27)	(103 $\pm$ 52)	(239 $\pm$ 124)	(184 $\pm$ 132)
Total	Number of Episodes	32	36	97	22	33	220
	Range (seconds)	14 – 386	36 – 781	13 – 1545	12 – 220	9 – 430	9 – 1545
	Mean $\pm$ SD	(56 $\pm$ 75)	(158 $\pm$ 191)	(159 $\pm$ 233)	(51 $\pm$ 50)	(86 $\pm$ 108)	(122 $\pm$ 186)

4.3 Machine learning approach of classifying travel patterns

Traditional machine learning algorithms are used to classify travel patterns from the obtained dataset in order to generate a comparison ground for our study.

4.3.1 Feature extraction

From the location sequence, we compute four representative features for each travel episode. The features are entropy (F1), repeated locations (F2), repeated directions (F3), opposite directions (F4).

The first feature, F1 measures the entropy of each episode. Entropy is the average information or unpredictability in a random variable. Therefore, entropy can be used to represent the randomness of movement in an episode.

The second feature, F2 aims to distinguish direct pattern from other types of patterns by counting the number of repeated locations in an episode. This is based on the fact that if a person keeps revisiting a number of locations in an episode of continuous movements, that episode is considered inefficient travel. Pacing and lapping patterns are repetitive movements in back-and-forth and circular manner. For these two types of patterns, not only are the locations of travel repeated but also the directions of movement (or travel). Therefore, we use two features, F3 and F4, to represent the repetitiveness of travel directions in each episode. Travel direction is the directional vector of two consecutive locations.

F3 counts the number of repeated travel directions in each episode. F4 counts the number of pairs of opposite travel directions. For example, in an episode, travel directions of two movements - one from location L_1 to location L_2 and another from location L_2 back to location L_1 - are considered a pair of opposite travel direction. Feature F4 is needed because the subject can pace and lap in opposite directions.

Now, we provide details on how the features are measured. Suppose that an episode with n -location sequence in a chronological order is represented as a vector $L = (L_1, L_2, \dots, L_n)$, whereas $L_i \neq L_{i+1}, i = \overline{1, n-1}$ and L_i are labels from Table 4.3.

From the vector L , we obtain:

- The direction vector $D = ((L_1, L_2), (L_2, L_3), \dots, (L_{n-1}, L_n))$
- The set of distinct elements in vector $L, S_L = \{L_i, 1 \leq i \leq n \mid L_i \in L\}$
- The set of distinct elements in vector $D, S_D = \{(L_i, L_{i+1}), 1 \leq i \leq n-1 \mid (L_i, L_{i+1}) \subseteq D\}$
- The frequency of occurrence of each element in $S_L, f_i = \frac{\text{number of occurrences of } L_i \text{ in } L}{n}, 1 \leq i \leq n$

Then, the four features are calculated as follows.

- Feature F1 is the entropy of the episode.

$$F1 = - \sum_{i=1}^n f_i \log f_i \quad (1)$$

- Feature F2 counts the total number of locations visited which are repeated. This is equal to the total number of elements n minus the number of unique elements in L (i.e. the cardinality of S_L).

$$F2 = n - \|S_L\| \quad (2)$$

- Similar to F2, F3 is calculated as:

$$F3 = n - 1 - \|S_D\| \quad (3)$$

- F4 is meant to distinguish travel in the same or opposite directions.

$$F4 = \|\{1 \leq i \leq n - 1 \mid \exists j, 1 \leq i < j \leq n - 1 \wedge L_i = L_{j+1} \wedge L_{i+1} = L_j\}\| \quad (4)$$

4.3.2 Feature selection and classification

4.3.2.1 Experiments and Evaluation

We have experimented with different combinations of the four features, and found that the best results were achieved by using all four features for classification. We tested eight classical machine learning algorithms including iNaïve Bayes (NB), Multilayer Perceptron (MLP), pruned Decision Trees (C4.5), Random Forests (RF), Logiboot (LB) and Bagging (BAG) with pruned C4.5 trees as base classifiers, k-Nearest Neighbor (k-NN) with one neighbor, and Support Vector Machine (SVM). All algorithms were tested using Weka freeware [113]. The best performing configurations of all the eight classifiers are also reported.

- NB classifier is based on Bayes's theorem with the assumption that the effect of a particular feature on a given class is independent of other features. It is made to simplify the computation involved and, in this sense, is called "naïve". Given a sample X , the classifier will predict that X belongs to the class having the highest posterior probability, conditioned on X . That is X is predicted to belong to the class C_i if and only if it is the class that maximizes $P(X|C_i)P(C_i)$. $P(C_i)$ is estimated by counting the frequency with which each class C_i occurs in the training data. Based on the assumption that features are independent given the class, $P(X|C_i)$ is the product of the probabilities for the individual features given class C_i [114].

- MLP is a neural network that mimics a neuronal organizational structure. It uses back propagation to train the network aiming to minimize the squared error between the network output and target values [115]. The network configuration used in our experiments is learning rate = 0.3, momentum = 0.2, epochs = 500.
- Decision Trees represent the set of classification rules in the form of a tree. It uses information gain to measure how well a given feature separates the training examples into their target class [116]. We used the J48 Decision Trees provided with the Weka software to classify travel patterns. The configuration used in our experiments is confidence factor = 0.25, the minimum number of instances per leaf = 2.
- RF is an ensemble classifier that consists of many Decision Trees and outputs the most popular class. A tree is grown from independent random vectors using a training set, resulting in a classifier. After a large number of trees is generated, random forest outputs the class that is the mode of the class's output by individual trees [117-118]. The configuration used in our experiments is the number of trees to be generated = 10, the random number seed = 1, the number of attributes to be used in random selection = 0.
- LB [119] and BAG [120] are ensemble methods that include multiple "base" classifiers, each of which covers the complete input space. Each based classifier is trained on a slightly different training set and the predictions or classifications of all classifiers are then aggregated to produce the single output. The simplest way to aggregate is to take a vote (e.g. a weighted vote). BAG and LB both adopt this approach but they derive the individual classifiers in different ways. In BAG, the classifiers receive equal weight, whereas in LB weighting is used to give more influence to the more successful classifiers. The base classifier used in experiments with BAG is the fast decision tree learner, and the model trees in experiments with LB used M5Rules.

- k-NN calculates instances using Euclidean distance and corresponds to points in an n-dimensional space. The algorithm assigns a class label to a data point that represents the most common value among the k training examples nearest to the data point [117]. We used k=1 in our experiment.
- SVM maximizes the margin between the training examples and the class boundary. SVM generates a hyperplane which provides a class label for each data point described by a set of feature values [121]. The kernel used in our experiments is the normalized poly-kernel.

The 10-fold stratified cross validation technique is applied and results are obtained in term of five validation metrics: precision, recall, specificity, F1-measure, and latency. The classification performance is based on individual episodes of movements, i.e. for each episode the classifier output is compared to the reference annotation (the ground truth).

For each type (class) of travel patterns, episodes which belong to its class (in the ground truth) are called “positives” and episodes not belonging to this class are called “negatives”. Then, “positive” episodes that are correctly (incorrectly) labeled by the machine learning algorithms are counted as True Positive (False Negative) (shortened as TP and FN) whereas “negative” episodes that are classified by the algorithms as “negative” episodes (“positive” episodes) are counted as True Negative (False Positive) (shorten as TN and FP). We measure: the precision (or Positive predictive value) $\left(Prec = \frac{TP}{TP+FP}\right)$, which represents the proportion of “positive” classified episodes that are relevant; the recall (True Positive Rate or sensitivity) $\left(Reca = \frac{TP}{TP+FN}\right)$, which measures how good the classifier is at detecting “positive” episodes; the specificity (or True Negative Rate) $\left(Spec = \frac{TN}{TN+FP}\right)$, which evaluates how good the classifier is at avoiding false alarms. F1-measure $\left(F1 = 2 \cdot Prec \cdot \frac{Reca}{Prec+Reca}\right)$ takes into account the precision and recall rate for each class. In addition, we evaluate the algorithms in terms of classification latency, which is the time delay between the start of a travel episode in the reference dataset and the start of a detected (classified) wandering episode by the application.

To report the overall performance metrics, we take the weighted average (or weighted arithmetic mean) of these measures from all classes, i.e. weighting the measure of each class of patterns by the proportion of instances there are in that class. This is done to avoid the problem of inflating the accuracy or recall values of classes with high recall values but few instances.

4.3.2.2 Feature Selection

As shown in Table 4.5 and Fig. 4.2, better results are obtained by using all four features. Thus features F1, F2, F3 and F4 are used in the subsequent experiments.

Table 4.5: Sensitivity and latency of the classification algorithms in each experiment

Classifier	Sensitivity or Recall		Latency (seconds)	
	Exp 1	Exp 2	Exp 1	Exp 2
NB	77.7	80	0.01	0.01
MLP	84.5	86.8	0.24	0.33
C4.5	90	91.4	0.01	0.01
RF	91.4	92.3	0.02	0.03
BAG	89.5	91.4	0.01	0.01
LB	91.4	91.4	0.03	0.05
k-NN	91.8	88.6	0.01	0.01
SVM	84.1	88.6	0.04	0.05

Exp 1: combination of features F2, F3, F4

Exp 2: combination of features F1, F2, F3, F4

Figure 4.2: Precision, specificity, and F1-measure of the classification algorithms in each Experiment (Exp 1: combination of features F2, F3, F4; Exp 2: combination of features F1, F2, F3, F4)

We also tried using common features including mean, standard deviation, and variance to classify travel patterns. Not surprisingly, these features do not represent the data well because the location labels do not capture the spatial relations of the physical locations.

4.3.2.3 Classification Results

We use confusion matrices to provide a more detailed picture of the errors generated by the classification process. The confusion matrices of the eight classifiers are given in Tables 4.6 and 4.7. The RF algorithm yields the best classification sensitivity or accuracy (92.3%). The RF algorithm indicated slightly higher accuracy compared to the Decision Trees algorithm. However, the Decision Trees algorithm is much simpler and transparent in decision making process compared to the RF. The RF algorithm introduces a much higher complexity in the decision making process, since the result is obtained using 10 Decision Trees and a mode voting procedure (i.e. the classified class is the mode of the classes output by individual trees).

The RF classification algorithm is also evaluated using the leave one subject out method. In each leave one subject out experiment, dataset of a subject is used for testing and the combined datasets of other four subjects are used for training. The sensitivity, specificity, precision, F-1 measures per subject, for each leave one out experiment, along with the average statistics are presented in Table 4.8. The weighted average accuracy for the leave one subject out experiment is 87.3%. Table 4.9 details the classification results of each class of patterns in the five leave one subject out experiments.

Table 4.6: Confusion matrices for NB, MLP, C4.5, and RF (GT: Ground Truth, CA: Classified As)

CA \ GT	NB				MLP				C4.5				RF			
	D	P	L	R	D	P	L	R	D	P	L	R	D	P	L	R
D	119	0	0	7	125	0	0	1	126	0	0	0	125	0	0	1
P	8	7	1	1	1	12	2	2	1	12	2	2	1	14	2	0
L	2	1	36	7	0	1	43	2	0	3	40	3	0	2	41	3
R	16	0	1	14	4	9	7	11	2	2	4	23	2	0	6	23

Table 4.7: Confusion matrices for BAG, LB, k-NN, SVM (GT: Ground Truth, CA: Classified As)

CA GT	BAG				LB				k-NN				SVM			
	D	P	L	R	D	P	L	R	D	P	L	R	D	P	L	R
D	124	0	0	2	125	0	0	1	125	0	0	1	120	0	6	0
P	1	12	2	2	1	12	3	1	3	12	1	1	1	12	3	1
L	0	2	41	3	0	3	39	4	3	2	39	2	1	1	41	3
R	2	0	5	24	2	0	4	25	8	0	4	19	3	0	6	22

Table 4.8: Leave one subject out results

Subject	Number of Episodes	Sensitivity	Specificity	Precision	Latency
1	32	1	1	1	0.01
2	36	0.833	0.937	0.862	0.01
3	97	0.897	0.974	0.924	0.01
4	22	0.727	0.606	0.813	0.01
5	33	0.909	0.929	0.928	0.01
Weighted Average		0.873	0.889	0.905	0.01

Table 4.9: Confusion matrices for leave one subject out experiment 1 with 3 features (top table) and experiment 2 with 4 features (bottom table) (GT: Ground Truth, CA: Classified As)

Subject CA GT	1				2				3				4				5			
	D	P	L	R	D	P	L	R	D	P	L	R	D	P	L	R	D	P	L	R
D	29	0	0	0	22	0	0	0	39	0	0	1	13	0	0	0	22	0	0	0
P	0	2	0	0	1	3	0	0	0	9	1	0	0	1	0	0	0	0	0	0
L	0	0	1	0	0	2	3	0	0	0	27	7	0	0	1	0	0	0	5	0
R	0	0	0	0	0	1	2	2	1	0	0	12	6	0	0	1	1	0	2	3

Subject CA GT	1				2				3				4				5			
	D	P	L	R	D	P	L	R	D	P	L	R	D	P	L	R	D	P	L	R
D	29	0	0	0	22	0	0	0	40	0	0	0	13	0	0	0	22	0	0	0
P	0	2	0	0	1	2	1	0	0	10	0	0	0	1	0	0	0	0	0	0
L	0	0	1	0	0	0	5	0	0	0	29	5	0	0	1	0	0	0	5	0
R	0	0	0	0	0	0	2	3	0	0	0	13	0	0	1	6	1	0	3	2

4.3.2.4 Discussion

4.3.2.4.1 Why does it work?

We use Fig. 4.3, 4.4 and 4.5 to explain why classifiers based on Decision Trees produce high accuracy in classifying travel patterns. Fig. 4.3 reproduces the pruned tree generated by the Decision Trees algorithm.

The leaves represent class labels or travel patterns, and branches represent conjunctions of features that lead to those class labels.

Figure 4.3: Pruned tree created by C4.5 algorithm

Fig. 4.4a shows the number of repeated locations of the entire 220 episodes. It clearly shows that direct episodes are distinguished from other episodes because the amplitudes of most direct episodes are zero. Direct patterns are efficient travel; therefore, it is highly likely that there is no repeated location in the sequence of locations of direct episodes. Hence, using F2, we can easily separate episodes into two main groups: direct (marked with yellow rectangle in Fig. 4.4a) and non-direct. The main task now is to classify pacing, lapping, and random from non-direct episodes. Using feature F1, we can discern pacing from lapping and random. Pacing is repetition movements between two locations. Therefore, the occurrence frequency of each location should be equal. Thus, the entropy of pacing episodes should be constant or

equal to one. This is obviously shown in Fig. 4.4b in which entropy of pacing episodes is one (marked with yellow rectangle) and entropy of lapping and random episodes is more than one.

(a) Feature F2

(b) Feature F1

Figure 4.4: Features F1 and F2 used in classifiers. In each figure, the horizontal axis represents the travel episodes (numbered from 1 to 220) with labeled patterns. The vertical axis of F1 displays the raw entropy value. The vertical axis of F2 displays the log value of the amplitude of each feature. (For F2, the amplitudes range from 0 to almost 100. Therefore, we use logarithm function to scale down the amplitude range of F2 for easy visualization. Since logarithm function is determined with only positive numbers, we add one to the raw amplitudes before taking logarithm)

The main task left now is to distinguish lapping and random from each other. Features F4 and F3 are mainly used for this task. In Fig. 4.5a, almost half of lapping episodes are separated from random episodes. They are episodes whose amplitudes of F4 are above 2. These episodes are highlighted in the yellow rectangle. Other lapping episodes, whose F4 values have the same amplitude range with the ones of random episodes, are highlighted in the purple rectangle (in Fig. 4.5a). We have to discern these lapping episodes from random episodes. Respectively, these lapping episodes are also indicated using the purple

rectangle in Fig. 4.5b. From Fig. 4.5b, we can see that the amplitudes of feature F3 of these lapping episodes are more than one whereas the ones of random episodes are almost zero or below one. Hence, we can classify these lapping and random episodes into their corresponding classes. The classified random episodes are marked with yellow rectangle in Fig. 4.5b.

(a) Feature F4

(b) Feature F3

Figure 4.5: Features F3 and F4 used in classifiers. In each figure, the horizontal axis represents the travel episodes (numbered from 140 to 220) with labeled patterns and the vertical axis displays the log value of the amplitude of each feature. (The amplitudes range from 0 to almost 100. Therefore, we use logarithm function to scale down the amplitude range for easy visualization. Since logarithm function is determined with only positive numbers, we add one to the raw amplitudes before taking logarithm)

4.3.2.4.2 Misclassifications and errors

In Tables 4.7, 4.8, and 4.9, the number of misclassified episodes are tabulated (non-diagonal elements).

Misclassifications are caused by three shortcomings of the employed algorithms. First, they are not able to handle several multi-pattern episodes. Second, the algorithms are not adaptive to learn/classify

episodes with few or almost zero training instances. Third, the algorithms do not incorporate contextual information (e.g. layout of the monitored area) to reason about the efficiency of travel episodes. Table 4.10 presents the percentage of misclassified episodes that are caused by each of the three shortcomings.

Table 4.10: Percentage of misclassified episodes caused by each shortcoming

Experiments	Shortcoming 1	Shortcoming 2	Shortcoming 3
C4.5	29.41%	35.29%	35.29%
RF	31.58%	52.63%	15.79%
Leave one subject out	32.00%	24.00%	44.00%

We give examples to illustrate these shortcomings. Examples of multi-pattern episodes are (dining, hall, dining, hall, toilet, hall, toilet) and (302, 301, bath, 301, 302, 303, hall, dining, hall, 303, 302). The first episode comprises two sub-patterns: pacing between the dining room and function hall, and pacing between the hall and the toilet. The second episode comprises two sub-patterns: lapping in the opposite direction between rooms 302, 301 and bath, and lapping in the opposite direction between rooms 302, 303, hall, and dining. In these two multi-pattern episodes, some locations (“hall” in the first episode, “302” and “303” in the second episode) belong to both patterns, which the Decision Trees based algorithms do not recognize. Therefore, these algorithms misclassified the first episode as “lapping” and the second episode as “random”. Another example is (ee, 303, 302, 303, ee, toilet, hall, ee, 303, 302, 301, 302, 303). 2 lapping sub-patterns (ee, 303, 302, 303, ee) and (303, 302, 301, 302, 303) are separated by a direct sub-pattern (toilet, hall, ee). However, the algorithms did not recognize these and misclassified as random.

Examples of misclassified episodes caused by the shortcoming 2 are (dining, hall, 303, hall, dining, hall, 303) and (C5306, AR2, NS, R5304, NS, CAR2, C5301, C5309, C5306, C5303). The employed algorithms are not able recognize the first episode as lapping in the same direction but misclassified it as pacing. We hypothesize that the algorithms recognized the repeated subsequences (dining, hall), and (hall, 303) in the first episode. However, they did not realize that these subsequences need to occur continuously in order to constitute a pacing pattern. Therefore, they misclassified it as pacing. In the second example, the

algorithms misclassified the random episode as lapping. Obviously, the second episode cannot be classified as lapping because there is no loop in the episode.

To rectify the first two shortcomings, we need to have an adaptive algorithm that is able to separate the individual sub-patterns, classify these sub-patterns accordingly and then aggregate them together so as to make the correct conclusion.

An example episode related to the shortcoming 3 is (R5304, NS, CAR2, C5309, AR2, C5303). The employed algorithms classify it as direct, which is not correct because it is indeed possible to reach the destination corridor C5303 from the room R5304 without going through locations NS and C5309. Therefore, it is an inefficient episode and should be classified as random. There are two approaches to detect such inefficiency. The first and direct approach is to base on the layout of the monitored area. If the layout shows there is a direct or more efficient path between C5303 and R5304, we can apply shortest path algorithms to find the direct path and make the conclusion. The second approach is applied when there is no layout or map available. In this case, we can base on the historical movements of the subjects to reason if there is a direct path between C5303 and R5304 or any other more efficient path, for instance (R5304, CAR2, AR2, C5303). This solution requires retrieving and searching previous episodes to detect such direct or more efficient paths. In this paper, we use the second approach to reason about this case because there is no layout available for the subjects monitored in the dementia care centre in Korea. Nonetheless, the second approach does not work for all the cases especially when there is no historical movement of the path needed to be searched or retrieved.

4.4 Deterministic Predefined Tree-Based Algorithm and Results

4.4.1 *Algorithm's design*

The goal of algorithm's design is to rectify the above shortcomings so as to improve the performance of Decision Trees algorithm.

4.4.1.1 Single-pattern and multi-pattern episodes

There are two cases: single-pattern episodes and multi-pattern episodes. A single-pattern episode has only one pattern from start location to end location. For example, episodes $L_1L_2L_3L_4$ or $L_1L_2L_3L_4L_3L_2$ are single-pattern because there is only one pattern appearing in the entire episode (direct for $L_1L_2L_3L_4$ and lapping for $L_1L_2L_3L_4L_3L_2$). An episode such as $L_1L_2L_3L_4L_3L_2L_3L_2$ is multi-pattern because there are two patterns, lapping ($L_2L_3L_4L_3L_2$) and pacing ($L_3L_2L_3L_2$) in the episode.

Since there is only one concluding pattern (direct, pacing, lapping, or random) in single-pattern episodes, we propose to design a sequential algorithm to do the classification. Technically, we assume that the sequential algorithm consists of four individual modules. Each module is responsible for classifying one type of pattern. By sequentially applying these modules, we are then able to classify single-pattern episode into the corresponding concluding pattern.

We consider each multi-pattern episode as a concatenation of single-pattern episodes. We can therefore apply the deterministic algorithm to classify the individual single-patterns or sub-patterns within a multi-pattern episode and aggregate these sub-patterns together to result in the concluding pattern.

To accomplish the proposed deterministic algorithm, there are three components needed to be addressed. First, we need to design modules or algorithms to check for direct, pacing, lapping, and random patterns. Second, we need to determine the sequence or the order of applying these modules to classify both single-pattern and multi-pattern episodes. Third, we have to propose an aggregation scheme for classifying multi-pattern episodes.

The objectives of the first and third components (individual modules and aggregation scheme) are quite clear and the details will be explained in next sections. In this paragraph, we illustrate why it is important to address the second component. If we imagine each module to check for each type of travel patterns is a leave in a tree, then determining the sequence of applying checking modules is indeed analogous to

determining the pruned tree in the Decision Trees algorithm. Different sequences might then produce different classification results and have different impacts. To illustrate this, we use episode $L_1L_2L_3L_4L_3L_2L_3L_2$, which could be classified as direct ($L_1L_2L_3L_4$) and pacing ($L_3L_2L_3L_2$), or lapping ($L_2L_3L_4L_3L_2$) and pacing ($L_3L_2L_3L_2$). If the sequence of applying checking modules is lapping first followed by direct and pacing, we will get two sub-patterns direct and pacing, which is incorrect because they do not recognize that this is a composite episode with common locations L_3 and L_2 . In other words, they do not rectify the first shortcoming. However, if the sequence of checking is direct first followed by lapping and pacing, it will yield correct results (lapping and pacing) and rectify the first shortcoming.

Theoretically, one can try all the enumerations of possible sequences but it is inefficient. We propose an effective approach to reason and identify the correct sequence of applying the checking modules. In the subsequent section, we first present the transformations of travel patterns. It describes how travel patterns evolve over time and space. Next we identify the sequence of applying checking modules. After that, we present the sequential algorithm in which the first and third components are detailed.

4.4.1.2 Transformations of travel patterns

There are four types of patterns or states. We have established the complete directed cyclic graph with four states (16 edges) to represent how patterns transform from one type to another type. The complete transitional state diagram is presented in Fig.4.6 with all 16 edges numbered.

Figure 4.6: Complete transitional state diagram

The criteria to prune out edges which are impossible to exist are as follows. A travel episode begins from a single start location. If the subject remains at the start location, it is a direct pattern itself. As the subject moves to new locations, the travel pattern could remain as direct or change to inefficient patterns. This explains why the edges 1, 2, 3, and 4 are retained. However, inefficient patterns cannot change back to direct pattern because they contain repeated locations, directions, or diversion. Hence, an episode always starts as direct and can evolve to inefficient travel but not the other way round. Therefore, the edges 7, 12, and 14 are removed.

By definition, pacing is a repeated path back and forth between two locations whereas lapping is a repeated circular path involving at least three locations. Thus, at least two consecutive locations must be repeated at least twice in order to constitute a pacing and/or lapping pattern. A path containing a sub-path of two consecutive locations that is repeated twice is already a random pattern (regardless of whether or not there is any sub-path or location between the repeated sub-paths). Such a path would remain as random or transit into pacing or lapping. Therefore, an inefficient pattern must be in the random state before it evolves into pacing or lapping. Due to this, we conclude that direct state cannot

change directly to pacing and lapping states. In addition, pacing and lapping patterns are subsets of random patterns. Hence, the edges 3, 4, 10, 15 are pruned while the edges 2, 5 are retained.

Subsequently, we explain why the edges 9, 11, 13, and 16 are retained. By definition, pacing and lapping contain repeated continuous paths between two or more locations. In a lapping/pacing episode, if such paths are repeated the pattern is unchanged. This explains why the edges 9 and 13 are retained. If a new path is visited during the episode, a new pattern, not necessary pacing or lapping, may be formed. In such cases, it would constitute a multi-pattern episode. If the new pattern is lapping or pacing, there is a partial partnership between the old lapping/pacing pattern with the new lapping/pacing pattern. The partnership is illustrated using two examples: $L_1L_2L_1L_2L_3L_4L_1L_2L_3L_4$ and $L_1L_2L_3L_4L_3L_2L_3L_2$. For the former, the sub-path L_1L_2 is part of a pacing pattern ($L_1L_2L_1L_2$) and a lapping pattern ($L_1L_2L_3L_4L_1L_2L_3L_4$). This showcases how a pacing state can partially transform to a lapping state. For the latter, the sub-path L_3L_2 is part of a pacing pattern ($L_3L_2L_3L_2$) and a lapping pattern ($L_2L_3L_4L_3L_2$). In this example, a lapping state partially transforms to a pacing state. The partnership also occurs between the old lapping (pacing) pattern and the new lapping (pacing) pattern. Examples are $L_1L_2L_3L_1L_2L_3$ $L_1L_2L_3L_1L_2L_3L_4$ $L_2L_3L_4L_2L_3L_4$ or $L_1L_2L_1L_2L_1L_2L_3L_2L_3L_2L_3$. Hence, the edges 11 and 16 are retained.

We then obtain the pruned state diagram shown in Fig. 4.7. The state diagram depicts the transformations from efficient to inefficient travels in an ambulation episode as the wandering subject moves from one location to another. The first movement from the start location initializes the state to direct. Depending on subsequent movements, the state may remain direct throughout the entire episode or change to random, then possibly followed by pacing or lapping. The state of the ambulation episode is continually updated until it reaches the end location. The final state label (e.g. random) is the episode's classification. For multi-pattern episodes, when a pattern is in pacing state, it either remains there or evolves to lapping and vice versa (Fig. 4.7). Table 4.11 illustrates the step-by-step process of classifying the path $L_1L_2L_3L_4L_3L_2$ as a lapping episode.

Table 4.11: State transformations of the ambulation episode L1L2L3L4L3L2

Step Number	Sequential Movements	state	Explanation
1	L ₁	direct	Direct pattern by definition.
2	L ₁ L ₂	direct	Direct pattern by definition.
3	L ₁ L ₂ L ₃	direct	Direct pattern by definition.
4	L ₁ L ₂ L ₃ L ₄	direct	Direct pattern by definition.
5	L ₁ L ₂ L ₃ L ₄ L ₃	random	Random pattern due to the repeated location L ₃ .
6	L ₁ L ₂ L ₃ L ₄ L ₃ L ₂	lapping	Lapping pattern due to the circular path L ₂ L ₃ L ₄ L ₃ L ₂ .

Figure 4.7: State diagram to demonstrate the transformation of travel patterns

4.4.2 Algorithm's formulation

4.4.2.1 The deterministic tree-based algorithm for classifying travel patterns

From the state diagram (Fig. 4.7) and the example in Table 4.11, we identify that we only need to have only three checking modules for the deterministic algorithm. These modules are to check for direct, pacing, and lapping patterns respectively. If an episode does not belong to any of the three patterns, it should be random. Based on this observation and the pruned state diagram, we formulate the sequence of applying checking modules as follows. The algorithm will first check if the episode is direct. If not, it is an inefficient travel pattern and the algorithm will check if the episode is pacing or lapping respectively. The ambulation episode is concluded as random if it is neither pacing nor lapping. In fact, this sequence

is highly similar to the pruned tree shown in Fig. 4.3 where direct pattern is examined in the zero level, followed by pacing and lapping in the second level, then random in the third level. In other words, the state diagram is agreeable with the empirical result produced by Decision Trees algorithm. Due to this result, we name the proposed algorithm as the deterministic tree-based algorithm.

A multi-pattern episode is considered as a concatenation of single-pattern episodes. To classify multi-pattern episodes, we also start by checking if the entire episode is direct. If not, we check for single-pattern episodes that are pacing. This is done by checking for the longest repeated pacing paths, e.g. “ $L_1L_2L_1L_2$ ” or “ $L_1L_2L_1L_2L_1L_2$ ”. Then, we will check for single-pattern episodes which are lapping. This is accomplished by checking for the longest circular paths (in both same and opposite directions). We will mark all the longest pacing and lapping paths as checked. For the remaining unchecked paths in the multi-pattern episode, we will label them as random if there are repeated locations and directions in those unchecked paths (by definition).

The aggregation scheme for multi-pattern episodes is designed as follows. We count the number of occurrence of each type of inefficient patterns for the entire multi-pattern episode. The concluding pattern is the one with the highest number of occurrence. If more than one inefficient patterns have the highest number of occurrence, the conclusion is drawn based on the severity of inefficient patterns (random, followed by lapping and then pacing).

Based upon the above analysis, the sequential tree-based algorithm (Algorithm 1) is formulated. Generally, mapping a single-pattern episode is a special case of mapping a multi-pattern episode. Algorithm 1 hence does not distinguish the two cases. To do the classification, the algorithm first checks for direct pattern. If it is indeed a direct pattern, then the episode is concluded as direct. Otherwise, it checks for pacing (line 3), lapping (line 4), and random (lines 5-9) patterns in the current episode and label them accordingly. The concluding pattern is identified based on the number of occurrence or the severity

of wandering patterns. The functions `isDirect()`, `checkPacing()`, `checkLapping()` are described in Algorithms 2, 3, and 4 respectively.

Algorithm 1 Classification of Wandering Patterns

Inputs:

- $L_1, L_2, \dots, L_n (n \in \mathbb{N})$: sequence of previously visited locations;

Output:

- pattern type (“direct”, “random”, “lapping”, or “pacing”) of ambulation $L_1, L_2, \dots, L_n$

```

1.  if (isDirect( $L_1, L_2, \dots, L_n$ )) label “direct” for the episode containing  $L_1, L_2, \dots, L_n$ ;
2.  else
3.    checkPacing( $L_1, L_2, \dots, L_n$ ) and label “pacing” for corresponding sub-patterns;
4.    checkLapping( $L_1, L_2, \dots, L_n$ ) and label “lapping” for corresponding sub-patterns;
5.    for each remaining unlabeled sub-sequence  $S_{ij}(L_i, \dots, L_j) (1 \leq i \leq j \leq n)$ 
6.      if (isDirect( $L_i, \dots, L_j$ )) label “direct” for  $S_{ij}$ ;
7.      else label “random” for  $S_{ij}$ ;
8.    endif
9.  endfor
10.  Ra, La, Pa = the number of sub-patterns labeled as “random”, “lapping”, and “pacing” respectively;
11.  max = Max(Ra, La, Pa);
12.  if (max == Ra) label “random” for the episode containing  $L_1, L_2, \dots, L_n$ ;
13.  else if (max == La) label “lapping” for the episode containing  $L_1, L_2, \dots, L_n$ ;
14.  else label “pacing” for the episode containing  $L_1, L_2, \dots, L_n$ ;
15.  endif
16.  endif

```

4.4.2.2 Algorithms to check for direct, pacing, and lapping patterns

4.4.2.2.1 Check for direct and non-direct patterns

A path including two or fewer movements is considered direct. Hence, Algorithm 2 detects a direct episode with more than two movements by checking if there is any repeated location in the episode (line 3) or any shorter or more efficient path that connects the start and end locations (lines 7-10). As mentioned earlier, we look for more efficient path from historical location sequences or episodes so as to rectify the third shortcoming.

Algorithm 2 `isDirect( $L_1, L_2, \dots, L_n$ )` : check if a travel pattern is of “direct” type

Inputs:

- $L_1, L_2, \dots, L_n (n \in \mathbb{N}, n > 3)$: sequence of previously visited locations;

Output:

- **true** or **false**: whether the pattern is “direct”

```

1.  for i = 1:n-1
2.    for j = i + 1:n
3.      if ( $L_i == L_j$ ) return false;
4.    endif
5.  endfor
6.  endfor
7.  search for paths containing  $L_1$  and  $L_n$  from previous location sequences
8.  if there is any more efficient path connecting  $L_1$  and  $L_n$  than the current path ( $L_1, L_2, \dots, L_n$ )
9.    return false;
10.  endif
11.  return true;

```

4.4.2.2.2 Check for pacing patterns

Checking for pacing is done by looking for the repeated pacing sub-pattern, e.g. “ L_1L_2 ”. The repeated sub-patterns must be continuous. Hence, we have to compare L_i with L_{i+2} and L_{i+1} with L_{i+3} (line 2). If $L_{i+2}L_{i+3}$ is the repeated pacing sub-pattern, we sequentially search for all the (continuous) pacing sub-patterns L_iL_{i+1} by using the pointer j (lines 3-8). We then label these pacing sub-patterns and update the search pointer i . L_{i+1} can be part of another pacing pattern, hence, we subtract 2 steps from the pointer j .

Algorithm 3 $\text{checkPacing}(L_1, L_2, \dots, L_n)$: search and label “pacing” if exist.

Inputs:

- $L_1, L_2, \dots, L_n (n \in \mathbb{N})$: sequence of previously visited locations;

Output:

- label “pacing” for “pacing” patterns

```

1.  for  $i = 1 : n - 3$ 
2.      if  $(L_i == L_{i+2} \&\& L_{i+1} == L_{i+3})$ 
3.           $j = i + 4$ ;
4.          while  $(j \leq n - 1)$ 
5.              if  $(L_i == L_j \&\& L_{i+1} == L_{j+1}) j += 2$ ;
6.              else break;
7.              endif
8.          endwhile
9.          label “pacing” for  $L_i \dots L_{j-1}$ ;
10.          $i = j - 2$ ;
11.     endif
12. endfor

```

4.4.2.2.3 Check for lapping patterns

By definition, a lapping pattern (e.g., $L_1L_2L_3L_4L_1L_2L_3L_4L_1$ or $L_1L_2L_3L_1L_3L_2L_1$) has its first location (L_1) repeated.

To look for a lapping pattern starting from an arbitrary location, we first sequentially search for the repeated locations of the arbitrary location (line 3). Algorithm 4 checks for circular paths in the same direction (lines 4-9), e.g. $L_1L_2L_3L_4L_1L_2L_3L_4L_1$ and those in opposite directions (lines 17-23), e.g. $L_1L_2L_3L_1L_3L_2L_1$. We use these example episodes to explain the algorithm.

For lapping in the same direction, once the repeated location (L_1) is found (line 3), the pointers i and j respectively index the first and fifth locations of the location sequence $L_1L_2L_3L_4L_1L_2L_3L_4L_1$. The repeated path (the second sub-sequence $L_1L_2L_3L_4L_1$ in the lapping pattern $L_1L_2L_3L_4L_1L_2L_3L_4L_1$) is detected by using a step pointer k , which moves through the location sequence to sequentially check for repeated locations (line 6). If there is any location mismatch, it will immediately terminate the while loop (line 7). The value of pointer k therefore indicates the length of the repeated path found. In line 10, we make use of this

length to determine that the repeated paths are continuous (to avoid cases such as two repeated paths $L_1L_2L_3L_4L_1$ are separated by another sub-pattern of different types, e.g. random). The condition $(i + k == j - 1)$ in line 10 is flexible enough to recognize lapping episodes such as $L_1L_2L_3L_4L_1L_2L_3L_4$ (when the first location is not revisited at last) or $L_1L_2L_3L_4L_1L_5L_1L_2L_3L_4L_1$ (when a single random location L_5 is visited during travel). Line 11 checks if the sub-paths found satisfy the condition of lapping (i.e. they contain at least three distinct locations). The variable `tempEnd1` is used to mark the latest location in the episode that has been labeled as lapping. This is to avoid repeated labeling.

In cases of lapping in opposite directions (e.g. $L_1L_2L_3L_1L_3L_2L_1$), the length of the location sequence is always an odd number. We use this characteristic to quickly examine if a pattern is a lapping in opposite direction (line 17). We indeed execute the checking for opposite paths (e.g. $L_1L_2L_3$ and $L_3L_2L_1$) similarly to what we do for detecting lapping in the same directions. However, we search for repeated locations in a reverse direction (line 20). We also use the condition in line 24 to check if the opposite sub-paths are continuous. Finally, we check if the sub-paths found satisfy the conditions for lapping (line 25) and use the variable `tempEnd2` to keep track of the latest location that is labeled as lapping.

Algorithm 4 `checkLapping( $L_1, L_2, \dots, L_n$ ):` search and label “lapping” if exist.

Inputs:

- $L_1, L_2, \dots, L_n$ ($n \in \mathbb{N}$): sequence of previously visited locations;
- *stack*: an empty stack data structure;
- `tempEnd1` = -1;
- `tempEnd2` = -1;

Output:

- label “lapping” for “lapping” patterns
-

```

1.  for  $i = 1:n-1$ 
2.      for  $j = i + 1:n$ 
3.          if ( $L_j == L_i$ )
4.               $k = 0$ ;
5.              while ( $i + k \leq j$  &&  $j + k \leq n$ )
6.                  if ( $L_{i+k} == L_{j+k}$ )  $k += 1$ ;
7.                  else break;
8.                  endif
9.              endwhile
10.             if ( $i + k == j$  ||  $i + k == j - 1$ )
11.                 if (tempEnd1 <  $j + k$  && isLapping( $L_i \dots L_{j-1}$ ))
12.                     label “lapping” for  $L_i \dots L_{j+k-1}$ ;
13.                     tempEnd1 =  $j + k$ ;
14.                     break;
15.                 endif
16.             endif
17.             if ( $(j - i) \% 2 == 0$ )
18.                  $k = i + 1$ ;

```

```

19.         while( $k < (i + j)/2$  &&  $k \leq n$ )
20.             if( $L_k == L_{j-k+i}$ )  $k += 1$ ;
21.             else break;
22.             endif
23.         endwhile
24.         if ( $k == (i + j)/2$ )
25.             if( $tempEnd2 < j$  &&  $isLapping(L_i \dots L_{j-1})$ )
26.                 label "lapping" for  $L_i \dots L_{j+k-1}$ ;
27.                  $tempEnd2 = j$ ;
28.                 break;
29.             endif
30.         endif
31.     endif
32. endif
33. endfor
34. endfor

```

The function `isLapping` checks whether or not the sub-path contains at least three distinct locations by subtracting the length of the location sequence by the number of unique elements or locations in the sequence.

Algorithm 5 `isLapping( $L_i \dots L_{j-1}$ )`: check if sub-sequence $L_i \dots L_{j-1}$ contains at least 3 distinct locations

Inputs:

- $L_i, \dots, L_{j-1}$ ($n \in \mathbb{N}$): sub-sequence to check;

Output:

- **true** or **false**: whether it contains at least 3 distinct locations

1. if ($j - i - uniqueElementsof(L_i, L_{i+1}, \dots, L_{j-1}) < 3$) return false;
 2. return true;
-

From the analysis of Algorithms 2-5, we can see that the complexity of Algorithm 1 is $\Theta(n^2)$.

4.4.3 Experiment and results

To have a fair comparison with other algorithms, we have applied the deterministic tree-based algorithm on the same test data of the 10-fold cross validation used in the machine learning approach. The sensitivity, specificity, precision, recall, F1-measure, and latency are 98.2%, 98.1%, 98.2%, 98.2%, 98.2%, and 0.0003s respectively. Results show that the deterministic algorithm improves both the classification recall and latency. In particular, the classification recall improves by 5.9% to 98.2% compared to the best result produced by RF. The latency is reduced remarkably to 0.0003s (100 times better than RF). The deterministic algorithm and the machine learning approach are compared using the McNemar's test [122] to examine if their differences in recall or accuracy are statistically significant. The results are depicted in

Table 4.12. It shows that the differences in classification accuracy of the deterministic algorithm and other eight classifiers are significant (p-Value is less than 0.01).

Table 4.12: Statistical comparison using McNemar's test (significance level = 0.01)

Classifier	NB	MLP	C45	RF	BAG	LB	k-NN	SVM
p-Value	<0.00001	0.00023	0.0003	0.003289	0.001156	0.0003	0.00013	0.00051
McNemar's value	36.21	17.93	13.07	8.64	10.56	13.07	19.05	16.41

Four misclassified episodes produced by the deterministic algorithm are due to shortcoming 2. The algorithm is not adaptive enough to recognize random patterns such as (CAR2, C5301, AR1, AR2) or (R5304, NS, CAR2, C5309, AR2, C5303). By using location context, it is possible to deduce that the corridors (CAR2, C5303) and the rooms (AR2, C5303) are near to one another. Therefore, such episodes are inefficient travel, not direct travel.

Additionally, we compare the capability of both the machine learning approach and the deterministic tree-based algorithm in the binary classification of direct versus indirect patterns. After all, pacing and lapping patterns are subsets of random patterns with different degrees of randomness or wandering. A simple direct/indirect classification is useful for providing healthcare practitioners a clear and quick assessment of the severity of a subject's wandering behavior.

Table 4.13 presents the binary classification performance. The results are improved for both approaches. For the machine learning algorithms, the sensitivity values of eight classifiers are improved from 5.6% to 7.8%. Meanwhile, the deterministic algorithm's sensitivity is increased by 0.4% only. Nonetheless, the deterministic algorithm produces the highest sensitivity (98.6%) and specificity (98.2%) with shortest latency. For machine learning approaches, the RF classifier yields the best classification results, which are 98.2% sensitivity, 97.8% specificity, and 0.01seconds latency. Nevertheless, the difference in performance between the two classifiers is not significant.

Table 4.13: Performance of machine learning approach and deterministic algorithm in classifying direct versus indirect travel

Classifier	Sensitivity	Specificity	Precision	Latency
NB	84.5	79.6	87.3	0.01
MLP	92.7	93.8	93.2	0.17
C4.5	97.3	96.9	97.3	0.01
RF	98.2	97.8	98.2	0.01
BAG	97.3	97.2	97.3	0.04
LB	97.7	97.5	97.7	0.06
k-NN	93.6	91.7	94.1	0.01
SVM	95.5	95.5	95.5	0.02
Deterministic algorithm	98.6	98.2	98.7	0.0003

4.5 Application of the Deterministic Predefined Tree-Based Algorithm

In this section, we present the deployment of the developed algorithm on a mobile device that is integrated with a WiFi-based localization system. We demonstrate that the mobile-health application can detect wandering patterns in real-time as the subject walks around his home environment. The application is also able to send an SMS alert to the attending caregiver once wandering is detected.

4.5.1 Architecture of the Mobile-Health Application

Fig. 4.8 shows the architecture of our WiFi-based mobile-health application to detect wandering patterns. The hardware components include 4 WiFi access points (Range-Pro), a smartphone (Samsung Galaxy 3 using Android 4.1.1 “Jellybean” Operating System), and the embedded phone sensors (accelerometer and compass). The smart phone can be placed in the elderly subject’s shirt pocket when he/she moves around.

Figure 4.8: Overall Architecture of the Mobile-Health Application

The software components include the location tracking module and the wandering detection algorithm (shown in red in Fig. 4.8). The phone scans for and obtains the RSSI (Received Signal Strength Indicator) values from the 4 access points. The RSSI values together with the acceleration and orientation signals from the phone sensors are used by the location tracking module to determine the subject's location. The wandering detection algorithm analyzes the locomotion data to detect and classify wandering patterns in real-time.

Figure 4.9: Actual Layout of the Home Residence (Fig. 4.9a) and its Sketch on the Mobile Phone (Fig. 4.9b)

Once wandering is detected, an alert message stating the location, time and pattern of the wandering episode will be sent to the caregivers or attending physicians via SMS. These details on the wandering behavior will enable caregivers or physicians to provide appropriate and timely interventions. The locomotion data and detected wandering patterns can also be stored in a database (e.g. the phone memory or a local computer server placed at home). The attending physicians can access the database to examine the wandering behavior and its progress over time, from which any changes in the subject's health and mental status can be recognized early.

The 4 WiFi access points are placed in the subject's home environment. Layout of the home residence where we have deployed the integrated system is shown in Fig. 4.9. Fig. 4.9a is the actual layout of the house (12.6m x 12.75m). Fig. 4.9b is the layout reproduced on the mobile phone for easy visualization.

The 4 green circles show where the 4 access points are located in the house. All the physical locations (e.g. bathrooms, living room, etc.) are also labeled accordingly in the figure.

4.5.2 Algorithms

In this section, we describe the algorithms we have developed to localize the subject and classify the wandering patterns as the subject moves around in the home residence.

4.5.2.1 Location Tracking Module

Our method relies on RSSI fingerprints to perform localization. We develop an Android application that scans for WiFi access points and obtain the RSSI values from each access point. The WiFi access points are placed at fixed known locations within the house and carefully spaced out (at least 3m apart). The RSSI map is established by collecting the RSSI values for 4 different directions (North, South, East, West) at every location. For reference, the arrow in Fig. 4.9b points to the North.

To improve the localization accuracy, we harness the phone's embedded sensors (accelerometer and compass). The usage of accelerometer is two-fold. Firstly, the acceleration value collected will help to determine if the subject is walking. This information in turn helps to decide whether or not to update the current location of the subject. Secondly, the acceleration value will also help to determine if the subject stops walking or is resting. This will mark the end of the ambulation or wandering episode (if the subject has been wandering). To minimize false detection of walking or resting (e.g. when the phone is shifted but no movement has occurred or when the subject stands up and sits down at one place), we first use a low-pass filter to isolate the gravity component of the acceleration magnitude and later remove it using a high-pass filter. Our experiment results show that the magnitude fluctuates between 0.04 and 0.25 while the phone is stationary. Thus, the walking magnitude threshold is set at 0.3 and any value registered above this threshold for more than 2 seconds will be deemed that the subject is walking.

The orientation sensor (compass) helps to determine the direction of movement. One of the problems of using RSSI fingerprints for localization is the RSSI values are very similar to each other at nearby locations. Therefore, with information regarding the direction of movement, we can narrow down the possible locations and subsequently determine the most probable location.

Upon launching the application, the system determines the start location and subsequently updates the location as the subject moves. To achieve this, the phone scans for access points and obtains the RSSI values at the frequency of 0.4 Hz. The obtained RSSI values are compared with the pre-collected ones (from the RSSI map) using L^2 -Norm measure to determine the possible locations. To increase the reliability, we reiterate the scanning and comparison steps for at least 3 times before establishing the start location. Subsequently, when the subject is deemed to be walking using values obtained from the accelerometer, the program retrieves the direction of movement from the orientation sensor to determine the next location (the one with least RSSI difference using L^2 -Norm measure).

4.5.2.2 Wandering Patterns Detection Algorithm

The wandering detection algorithm classifies the movements into corresponding patterns: direct, random, pacing, lapping. The wandering patterns detection algorithm used is the deterministic predefined tree-based algorithm that we describe in the section 4.4.

4.5.3 Evaluation and Discussion

4.5.3.1 System Performance

The above algorithms are integrated and installed on a smart phone. To evaluate the performance, a study subject carries the phone (by either holding it in the palm or putting it in the pocket) and executes 40 pre-defined walking paths. As the subject walks, the mobile application detects wandering patterns in real time, displays the results on the phone screen, and logs all the details (time, locations and patterns

detected). The detected patterns are compared with the ground truth (established by manually classifying the patterns based on the pre-defined walking paths) for evaluation.

Table 4.14: Performance Results of 40 Walking Exercises

Patterns	Total Number of Patterns in Ground Truth	Patterns Detected by the Program		
		Total Number	Correct Detection	Incorrect Detection
Direct	11	16	11	5
Random	13	8	8	0
Pacing	12	12	12	0
Lapping	11	11	11	0

Table 4.14 summarizes the performance results of 40 walking exercises. In Table 4.14, the patterns, correct and incorrect detection results are color coded for easy verification. The recall value ranges from 61% (8/13 for random) to 100% (12/12 for pacing and lapping). In all the misclassifications, random patterns are classified as direct (5 cases). We will discuss these cases using the examples in Fig. 4.10.

Fig. 4.10 shows examples of wandering and non-wandering patterns detected by our application. Blue lines represent forward movements (step forward) or right turns whereas red lines represent backward movements (turn back and step forward) or left turns. Yellow circle represents the start location and yellow arrow shows the current direction the subject is heading. The white color text displays the time and location captured by the tracking module and also the corresponding wandering pattern (capitalized text) classified by the wandering patterns detection algorithm. The locations displayed in Fig. 4.10 are abbreviated by taking the first 3 characters of the labels in Fig. 4.10, except that living room regions 1-6 are displayed as LivR1-6 respectively.

In Fig. 4.10a, the subject wanders from the kitchen to the bedroom 3. He laps around in the living room, then paces around the balcony1 and lingers randomly around the house entrance in the living room before reaching the bedroom3. Fig. 4.10b shows that the subject walks directly from bedroom 2 to the study room. This is not considered wandering; hence, the pattern (Direct) is not displayed with the text.

Figure 4.10: Screen Capture of Test Cases from the Phone

Fig. 4.10c also showcases a walking path from bedroom 2 to the study room. However, the subject does not move efficiently in this case. He passes through living room regions 6 and 3 unnecessarily (without doing anything there). This is classified as a random movement in the ground truth but the application detects it as direct. Similarly, in Fig. 4.10d and 4.10e, the subject walks from the kitchen and the study room to bedroom 3 respectively. He wanders in the living room and the balcony 1 and 2 before reaching the destination. Our application does not recognize these as wandering patterns (random) because there is no repetitive path in his travels. Therefore, it considers these cases as efficient travel patterns (direct). To rectify these misclassifications, we have to incorporate the layout of the monitoring area in our wandering detection algorithm. In fact, if the layout of the house is incorporated, the application can apply shortest path algorithm to reason that the most efficient path from bedroom2 to the study room should be the one shown in Fig. 4.10b. Hence, by comparing the most efficient path and the actual travel path (e.g. Fig. 4.10c), the application can detect whether or not the subject is wandering. Similarly, the

application will also be able to detect the sub-paths from living room region 5 to balcony1 and then to balcony2 (in Fig. 4.10d and 4.10e) are inefficient travels (or wandering).

4.5.3.2 Discussion

Table 4.15 compares our system (WiFi+ Phone) with other 2 commercial systems that have been used to detect indoor wandering locomotion for PWD. The first is a UWB cum WiFi based system (Ubisense [31]) and the second is an RFID based system [77, 79].

Table 4.15: Systems' Comparison

Performance Criteria	Ubisense	RFID (POWERTAG)	WiFi + Phone
Localization Accuracy	15 cm	2-3m (Physical Rooms)	2.5m (Physical Rooms)
Equipment Cost	7484 USD	11600 USD	800 USD
Scalability	Yes but costly	Yes and convenient	Yes but challenging
Non-Intrusiveness	Yes (wearable tags)	Yes (wearable tags)	Limited (mobile phones)
Ability to Detect Wandering Patterns	Not integrated	Not integrated	Integrated

Compared to the other 2 systems, our solution is more cost-effective in terms of equipment (i.e. excluding software, installation, maintenance and support services). For Ubisense, the projected cost includes a tag and 4 sensors. For POWERTAG, the cost includes the price for a single unit of RF tag, receiver, antenna, trigger generator, trigger antenna, tag checker and tag battery charger. Our system cost is mainly for the 4 access points and the mobile device. The other two systems have been used to collect locomotion data of PWD in nursing homes; however, they still heavily rely on human coders to recognize wandering patterns. Meanwhile, our proposed software system is integrated with the ability of detecting wandering patterns. All three systems are able to provide graphical display of user movements on the interface for monitoring purposes. Ubisense is a commercial system that provides very accurate location data (15cm-30cm) but it is very costly to scale up. The reasons are because Ubisense is a wired (not wireless) and line-of-sight system. Hence, for surveillance of two separate bedrooms, the number of sensors required and the costs will be doubled. Our proposed system can be scaled up by having more WiFi access points installed; however, the complexity, cost of calibration and computation will also increase. Compared to

Ubisense and our system, POWERTAG is more convenient to scale up for larger monitoring area by having more antennas or higher resolution. Both Ubisense and RFID attach wearable tags of small dimensions (83mm x 42mm x 11mm for Ubisense tag and 28mm x 42mm x 6.8mm for RFID tag) to the subjects for monitoring purposes. Our application assumes the subject to be carrying a mobile phone when he/she moves around. In reality, it may be difficult for PWD to comply with this requirement due to their illness. To enhance the practical feasibility of our proposed solution, the mobile phone can be replaced by a compact wearable circuit tag that only incorporates accelerometer, orientation sensor and WiFi.

Chapter 5 Wandering Patterns Classification Using Time-Series Representation

This chapter includes three sections. Section 5.1 introduces the motivation of using time-series inertial information in detecting travel patterns. Section 5.2 details the results of using traditional time-series classification algorithms to classify travel patterns. We also describe an improvised representation of inertial signals and its advantages in classifying travel patterns. Section 5.3 presents a new algorithm we develop to classify travel patterns using inertial information. We also present the results and lessons learnt from the experiment on both dementia and non-dementia persons.

5.1 Motivation

From the experience in developing the location tracking module for the mobile-health in Chapter 4, we observe that we use inertial sensors (accelerometer and magnetometer) unobtrusively attached to PWD to track the person's orientation in order to determine the travel patterns. Accelerometers measure both translational acceleration of the object and acceleration due to gravity. The magnetometers are a type of electronic compass that can determine the orientation of a device relative to the earth's frame of reference (specifically, magnetic north). Using these two hardware sensors, we can identify (a) whether a person is walking or not, and (b) the orientation if he/she is walking. The orientation information is both necessary and sufficient for detecting travel patterns. We will elaborate on the observation.

Inertial sensors provide orientation data in three dimensions: azimuth (degrees of rotation around the z axis), pitch (degrees of rotation around the x axis), and roll (degrees of rotation around the y axis). Our approach only requires the azimuth, which is the angle between magnetic north and the device's y axis. This value is 0 when the device's y axis is aligned with magnetic north. The value is 90, 180 and 270 when the y axis is pointing east, south and west respectively.

Figure 5.1: Example of wandering patterns. The arrows with dash-line depict the path taken by the subject within an area. The graph associated with each pattern shows the instantaneous azimuth value for each sampled data point (frequency = 20Hz) as the person moves

Fig. 5.1 gives one example each for the four travel patterns: direct, pacing, lapping, and random. For each pattern, we plot the azimuth values (or orientation signals) as the person travels. The orientation signals are distinct for each travel pattern. When the person walks directly, the signal is fairly constant. When the person paces, the signal is constant for a short duration as the person walks directly, then sharply changes by 180 degrees when the person turns around. This sequence is repeated if the person continues to pace. For lapping, the signal rises slowly from the current value to 360 degrees then drops sharply to 0 degree. This repeats if the person laps in the same direction. If the person laps in the opposite direction instead, the signal will drop slowly but rises sharply. The two different directions of lapping can therefore be distinguished. When a person walks randomly, then the signal changes in a random manner. These observed characteristics of the signals are key features to develop our recognition algorithms.

5.2 Using Traditional Time-Series Approach to Classify Travel Patterns

In this section, we aim to use time-series approach to classify travel patterns including direct, pacing, lapping, and random.

5.2.1 Experiment Design

This section presents the controlled experiment that was conducted to collect data for our study. The travel patterns were controlled in this experiment in the way that the data collector personnel informed the recruited subjects of the patterns that were deemed to be collected before the actual collection took place. Details of the experiment are elaborated as follows.

5.2.1.1 Apparatus

We used a smart phone device (Samsung I9500 Glaxy S4) to collect inertial data. An Android application was developed and installed on the smart phone device to log the following inertial data: timestamp (ms), acceleration force along the x axis including gravity (m/s^2), acceleration force along the y axis including gravity (m/s^2), acceleration force along the z axis including gravity (m/s^2), linear acceleration of the device (m/s^2), orientation of the device or the angle between magnetic north and the device's y axis (degree). The data sampling rate was 20 Hz.

5.2.1.2 Subjects

14 non-dementia subjects were recruited from the university campus and laboratory. The criterion for inclusion is the subject is mentally healthy and capable of independent ambulation. The data collection exercise was approved by the Institutional Review Board (IRB) of NTU. The research objectives were explained to each subject and their consent to participate in the research was obtained before collecting the data. Table 5.1 summarizes the descriptive statistics of the 14 subjects.

Table 5.1: Characteristics of the 14 non-dementia subjects

Variables	n = 14	
	Percentage (%)	Mean $\pm$ SD
Age (years)		38.5 $\pm$ 15.2
Sex		
Male	64.0	40.0 $\pm$ 15.4
Female	36.0	35.8 $\pm$ 16.2

5.2.1.3 Procedure

Before the collection exercise, subjects were explained and given examples on each type of travel pattern including direct, pacing, lapping, and random. To confirm their understanding, each subject was asked to replicate each pattern once before the actual data collection.

For this study, the 14 non-dementia subjects held the mobile phone on their hand (palm facing up). This was more convenient for the subject to interact with the user interface on the phone screen to start/stop logging the data. To ensure data quality, the subjects were instructed not to change the direction of holding the phone during data logging. So, the phone was held in the horizontal position, i.e. parallel to the ground with the screen facing upwards.

During this collection exercise, the data collector personnel first informed the subjects of the travel patterns that were deemed to be collected. The subjects would then be expected to walk in the corresponding manner. During the walk, the subjects carried a smart phone device with the data logging application installed. When the subjects started walking, they clicked on a toggle button on the phone screen to trigger data logging and the inertial data of that travel episode would then start logging. When the subjects stopped walking, they toggled the button to stop data logging for that travel episode. The inertial data would be then automatically stored as a text file in the phone. To ensure data quality and correctness, the subjects' movements during their walk were closely monitored and observed. If the travel patterns exhibited by the subjects did not agree with what we planned to collect, the data would then be discarded.

This data collection exercise was carried out in the open air basement of the school building. There was no restriction on the paths that the subjects should walk or on the number of episodes that each subject must walk. Each subject was free to walk (including pause and stop sometimes) in the expected pattern

on their own in the open area of 15m x 10m. Overall, the path length of each pattern ranges from 4m (e.g. direct) to 25m (e.g. lapping or random) and the average path time is 11 seconds.

In Table 5.2, we summarize the number of travel patterns in each category (direct, pacing, lapping, random) that we collected from 14 volunteer subjects. The dataset is available upon request.

Table 5.2: Statistics of dataset collected from 14 non-dementia subjects

Subjects	Male/Female	Age	Direct	Pacing	Lapping	Random	Total
1	M	26	28	25	34	27	114
2	M	55	32	28	25	27	112
3	F	24	25	29	31	19	104
4	F	54	7	28	52	37	124
5	F	24	4	11	8	6	29
6	F	24	25	25	26	25	101
7	M	22	25	25	25	25	100
8	M	59	25	26	26	25	102
9	F	53	27	25	26	27	105
10	M	24	25	25	26	25	101
11	M	55	7	4	4	3	18
12	M	30	50	50	50	50	200
13	M	35	39	18	20	23	100
14	M	54	7	11	14	12	44

5.2.2 Time-Series Classification Approach

Two popular time series methods are used to classify the travel patterns collected from 14 non-dementia subjects. The first algorithm uses dynamic time warping (DTW) [123] to compute the similarity of two time series. Classification is done by computing the similarity of a time series with all other time series of known classes. The class to which the most similar series belongs is determined as the answer. The second algorithm or well-known as Symbolic Aggregate approximation (SAX) [124] has the same working principle as the first one but it transforms the original time series into symbolic strings before using DTW or other distance measure to compute similarity scores and voting.

Fig. 5.2 [124] explains the SAX representation of the time-series signal. First, it reduces the time series dimensions by dividing the sample data into equal sized “frames”. In the example, the original data of dimensions $n = 128$ is reduced to $w=8$ dimensions of same size (frame size = 16). The mean value of the data falling within a frame is calculated and a vector of these values becomes the data-reduced representation. The representation can be seen as a piecewise aggregate approximation (PAA) of the original time series with a linear combination of box basis functions as shown in Fig. 5.2a. Then, a further transformation is done to obtain a discrete representation by determining the “breakpoints” that will produce equal-sized areas under Gaussian curve of the time-series amplitudes (the vertical axis). Gaussian distribution is used because it is desirable to have a discretization technique that will produce symbols with equiprobability. By using 3 “breakpoints”, the original time series is mapped to the word baabccbc (Fig. 5.2b).

Figure 5.2: a) Piecewise Aggregate Approximation representation of the time-series signal b) SAX representation of the time-series signal

We normalize the orientation time-series signals from the inertial data of 14 subjects to have a mean of zero and a standard deviation and apply the DTW and SAX algorithms on the normalized orientation signals to classify the travel patterns collected. The available toolkit [125] developed by the author of SAX representation was used. Each subject's dataset is split into training and testing parts of almost equal size so as to avoid overtraining and long training time due to the fact that each testing series is compared with each and every series in the training set to find the closest match. The selection of training and testing sets is done randomly using the 2-fold cross-validation function in MATLAB. This methodology is adopted from previous time-series classification problems [124].

Table 5.3: Classification Results using SAX and DTW (D=Direct, P=Pacing, L=Lapping, R=Random)

Subjects	Training Set					Testing Set					SAX		DTW	
	D	P	L	R	Total	D	P	L	R	Total	Recall	Time	Recall	Time
1	14	13	18	13	58	14	12	16	14	56	58.9	8.42	53.6	114.27
2	14	13	14	16	57	18	15	11	11	55	65.5	8.50	53.8	69.00
3	12	13	19	7	51	13	16	12	12	53	64.2	8.27	59.0	109.24
4	3	13	28	18	62	4	15	24	19	62	64.5	10.28	64.0	350.15
5	2	5	4	3	14	2	6	4	3	15	73.3	0.62	53.8	4.70
6	13	12	14	13	52	12	13	12	12	49	75.5	6.87	67.1	14.57
7	13	12	13	12	50	12	13	12	13	50	86.0	6.74	64.2	11.66
8	14	14	10	12	50	11	12	16	13	52	69.2	6.95	68.0	31.53
9	14	10	16	14	54	13	15	10	13	51	60.8	7.45	69.5	19.95
10	14	13	13	9	49	11	12	13	16	52	84.6	6.96	75.2	60.27
11	5	2	2	1	10	2	2	2	2	8	50.0	0.22	57.6	3.31
12	25	25	25	25	100	25	25	25	25	100	57.0	27.81	54.2	485.18
13	22	9	8	11	50	17	9	12	12	50	50.0	6.70	45.8	230.59
14	2	5	7	8	22	5	6	7	4	22	54.5	1.37	41.9	47.37

We use the training part to search the best value for SAX parameters w (number of SAX words) and a (size of the alphabet). For w , we search from 8 up to $n/2$ (n is the length of the time series). Each time we double the value of w . For a , we search each value between 4 and 8. If there is a tie, we use the smaller values. Empirically, $w=32$ and $a=6$ are the set of parameters that produces the best classification accuracy (recall). Then we classify the testing set based on the training set using one nearest neighbor classifier and report the results. Table 5.3 details the number of training and testing patterns in each category (direct, pacing, lapping, random) that were used in our experiment. The classification recall (%) and classification time (seconds) for each subject's dataset are also reported. The classification recall is the true positive rate or sensitivity. The classification time is the time the classifier takes to completely classify the testing set of each subject. In general, SAX is better and more efficient than DTW in identifying travel patterns. The time and space efficiency of SAX results from its dimensionality reduction capability.

5.2.3 Improvised Representation of Orientation Time-Series Signals

Inspired by the PAA and SAX representation, we develop an improvised representation to detect travel patterns using orientation signals. We reverse the steps in SAX representation by performing the discretization transformation first and later reducing the dimensionality. The motivation for doing so is explained in the following examples in Fig. 5.3 and Fig. 5.4.

Figure 5.3: Example 1

We observe that the orientation signals are likely to be of square wave forms. In reality, people usually walk a straight line for certain time (at least a few seconds) before they make a direction change. Rarely do humans change the travel direction every second during walking unless they exhibit lapping. The orientation signal during a straight walk is highly likely to be uniform since the orientation variance should be close to zero. The orientation variance is significant at the point in time where the person makes a direction change. Hence, if we view the travel path as the concatenation of multiple straight walking paths, the orientation signals of an entire travel episode (from the time the person starts walking till the time he/she stops walking) will tend to be of square wave forms. This is illustrated in Fig. 5.3b (the black line) using a sample walking path of a person from point A to point E in Fig. 5.3a. As the orientation signals tend to be uniform between the two consecutive direction changes, aggregating the signals using equal sized

“frames” before discretization is not useful most of the time. In fact, in the ideal situation whereby the durations of each straight walking episode are the same (i.e. if $t_B - t_A = t_C - t_B = t_D - t_C = t_E - t_D$), such aggregation is not necessary if the frame size happens to be equal to the duration times the sampling rate. In other cases, it could reduce the information regarding direction changes. In Fig. 5.3b, if the frame size is selected as shown, it could result in a situation whereby the same walking direction in a long straight sub-path (e.g. from C to D) in the original signal is represented by two different symbols in the SAX representation. It could also result in two different walking directions (A to B and B to C) being represented by the same symbol.

Figure 5.4: Example 2

In Fig. 5.4, we illustrate the case when the person makes a change in direction of walking instantly (e.g. when the person laps around a place). In this case, the orientation signal tends to be linear. Hence, if the person laps in a small circle, aggregating the orientation signal using a large frame size could result in the whole episode of lapping to be represented by a single symbol.

5.2.3.1 Reverse-SAX representation of orientation time-series signals

Based on the above observations, we devise an improvised representation named reverse-SAX by first discretizing the orientation signal in order to maintain the information of travel direction. Unlike SAX, we

select the “breakpoints” on the amplitude axis to be of equal-distance. For example, if we want to represent the North, South, East, West directions (or 4 symbols), we could use 4 “breakpoints” whose values are 45° , 135° , 225° , 315° respectively. Orientation values belonging to $[45, 135)$, $[135, 225)$, $[225, 315)$ will correspond to the North, West, South directions. Values less than 45 or more than 315 will correspond to the East direction.

After discretization using “breakpoints” of equal-distance, we apply PAA on the discretized signal to reduce the dimensionality. However, we do not divide the signal into equal size “frames” like PAA. We divide the discretized signal into frames of different sizes by finding the points where there is amplitude change. We achieve this by first applying a low pass filter on the discretized signal and later doing differentiation on the filtered signal. The purpose of applying the low-pass filter is to remove the spikes in the discretized signal. Differentiation is applied because the differentiated values at the points of amplitude change will be non-zero. Using these non-zero crossing points, we can divide the discretized signal into frames of different sizes each of which has the same discretized value. Hence, by using the amplitude and the size of each frame, we can reduce the dimensionality of the original signal by representing it with a linear combination of pairs of discretized amplitude and frame size.

5.2.3.2 Experiment results of classification using reverse-SAX representation with k-NN

We apply reverse-SAX representation to the orientation signals of 14 subjects in Section 5.2.1.2. To compare the performance of reverse-SAX with SAX and DTW, we use the same testing set described in Section 5.2.2 and apply one nearest neighbor classifier to classify the patterns. We experiment reverse-SAX with $a=4$, $a=6$, and $a=8$ and report the results. Table 5.4 describes the “breakpoints” and discretized values used with alphabet size of 4, 6, and 8 respectively.

Table 5.4: Reverse-SAX representation with $a=4$, $a=6$, $a=8$

Number of alphabets	“Breakpoints” values (in degree)	Discretized values
$a = 4$	0, 90, 180, 270, 360	1, 2, 3, 4

a = 6	0, 60, 120, 180, 240, 300, 360	1, 2, 3, 4, 5, 6
a = 8	0, 45, 90, 135, 180, 225, 270, 315, 360	1, 2, 3, 4, 5, 6, 7, 8

The classification results are summarized in Table 5.5. In general, reverse-SAX outperforms both SAX and DTW in terms of classification accuracy and efficiency. On average, the best performance accuracy is obtained with $a=6$. The mean differences in performance recall of reverse-SAX and SAX and DTW are 13% and 18% respectively. In addition, reverse-SAX is almost 7 and 110 times faster than SAX and DTW in classifying the travel patterns. The results from Table 5.5 show that reverse-SAX is able to further reduce dimensionality and better represent the orientation signals compared to SAX and DTW.

In Table 5.5, we also present the results of experiment with Reverse-SAX when there is no dimensionality reduction and $a = 360$. This is a special case which is a close approximation of DTW even though it is not exactly the same as DTW because the orientation can take any real values from 0 to 360 degree. The results show improvement in classification recall as compared to the original DTW approach. As expected, the classification time is significantly increased as compared to reverse-SAX with dimensionality reduction. In terms of classification recall, reverse-SAX with dimensionality reduction ($a=6$) still outperforms the one without dimensionality reduction in general. In particular, the number of subjects or cases whereby reverse-SAX ($a=6$) outperforms, underperforms, and equally performs reverse-SAX ($a=360$) are 10, 2, and 2 respectively. Using a sign-test ($n=12$, number of successes =2) to test the hypothesis whether the difference in performance is significant, we can obtain the p-value = 0.016, i.e. the performance difference is significant. The above analysis once again affirms that reverse-SAX outperforms DTW in our experiments, especially in terms of classification time.

Table 5.5: Classification results of reverse-SAX, SAX, and DTW

Subjects	SAX	DTW	Reverse-SAX	Reverse-SAX (no
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											dimensionality reduction)	
					a=4		a=6		a=8		a=360	
	Recall	Time	Recall	Time	Recall	Time	Recall	Time	Recall	Time	Recall	Time
1	58.9	8.42	53.6	114.27	75.0	1.75	75.0	2.32	69.6	2.52	67.9	99.95
2	65.5	8.50	53.8	69.00	67.3	1.07	69.1	1.29	76.4	1.42	69.1	72.16
3	64.2	8.27	59.0	109.24	67.9	1.06	71.7	1.36	71.7	1.46	79.3	114.39
4	64.5	10.28	64.0	350.15	82.3	1.87	87.1	2.53	85.5	2.88	80.7	363.04
5	73.3	0.62	53.8	4.70	86.7	0.10	93.3	0.12	86.7	0.16	86.7	4.52
6	75.5	6.87	67.1	14.57	87.8	0.84	83.7	0.99	79.6	1.15	79.6	14.19
7	86.0	6.74	64.2	11.66	94.0	0.69	90.0	0.88	82.0	0.98	88.0	12.44
8	69.2	6.95	68.0	31.53	82.7	0.71	80.8	0.91	86.5	1.07	71.2	29.78
9	60.8	7.45	69.5	19.95	74.5	0.84	78.4	1.06	72.5	1.29	76.5	19.27
10	84.6	6.96	75.2	60.27	78.8	0.75	84.6	0.92	71.2	1.08	80.8	59.48
11	50.0	0.22	57.6	3.31	75.0	0.03	75.0	0.03	37.5	0.03	37.5	3.33
12	57.0	27.81	54.2	485.18	70.0	3.43	75.0	4.60	74.0	5.21	80.0	493.92
13	50.0	6.70	45.8	230.59	78.0	0.85	74.0	1.05	72.0	1.35	64.0	231.67
14	54.5	1.37	41.9	47.37	59.1	0.20	59.1	0.25	63.6	0.41	59.1	47.99
Average	65.3	7.66	59.1	110.84	77.1	1.01	78.3	1.31	73.5	1.50	72.9	111.87

5.3 Reverse-SAX Based Algorithm

Even though using reverse-SAX and one nearest neighbor classifier has improved the capability in classifying travel patterns, it is challenging to actualize it on a large number of user population because training data is required for traditional classifiers such as nearest neighbor. It is difficult to obtain the training data for each user especially PWD. In addition, there is a question on the amount of required training data in order to achieve satisfactory and reliable classification. Scalability is another challenge. Therefore, it is desirable to have a scalable classifier that requires virtually no training data but is able to capture the universal characteristics of travel patterns across different people. This Section presents the design of such algorithm and reports the performance of the algorithm on the collected datasets.

5.3.1 Reverse-SAX Based Algorithm (RSAX)

We harness the working principle of the deterministic tree-based algorithm presented in Chapter 4 and apply Reverse-SAX representation to design an algorithm that is able to capture travel patterns including wandering yet requires no training data. The algorithm details are explained as follows.

Step 1: We apply the reverse-SAX representation to the orientation signal. By applying reverse-SAX, the directions of travel (the discretized amplitudes or values) and the time spending in each direction (the window or frame size) are known. We use the reverse-SAX representation signal in the subsequent processing steps.

Step 2: We use the information of the time spending in each direction to determine the major travelled direction, which is defined as the direction in which the person spends at least 70% of traveling. If the major travelled direction exists, we ignore all other travelled directions and conclude that the pattern travelled is direct.

If no major direction is found, we will look at the distribution of all the travelled directions according to the window sizes. If they are uniformly or normally distributed, we will also consider this as a direct pattern. Or else, we will classify this pattern as non-direct and further process in the subsequent steps 3 and 4 in order to arrive at the concluding pattern. Detection of uniform distribution is done by using a simple chi square test or Kolmogorov Smirnov test. We used Kolmogorov Smirnov test because it looks at the whole distribution and non-parametric whereas chi square test is simple but depends on asymptotic distribution.

In steps 3 and 4, we determine if the pattern is pacing or lapping.

Step 3: For pacing patterns, the problem is to detect the paths where the person repeats walking in opposite directions (refer to the definition of pacing). Strictly speaking, if we plot the normalized (zero mean) orientation signal of an ideal pacing pattern where the person walks in opposite directions

repeatedly, we can see that it can be formally modelled by a square wave with 180° amplitude. To determine a pacing pattern, it is therefore to search the reverse-SAX representation signal for any 2 consecutive travelled directions of same frame sizes with a difference in orientation values of 180° . We use a simple fitting model to determine pacing. The model is similar to the function of a square-wave signal; but, the min and max values here are 0 and 180 instead of 0 and 1. The width of the each square wave represents the duration of straight walk before and after the 180° turn. Model fitting is done by applying least square regression method on the reverse-SAX representation signal to find the parameters representing the duration of the 180° if it is fitted. Coefficient of determination (R^2) was used to evaluate the quality of the model fit or basically to accept or reject the found fit. If accepted ($R^2 > 0.99$), it is determined as pacing. If not, we continue with Step 4 to check for lapping.

Step 4: For lapping patterns, the challenge lies in the polymorphisms of a circular lap (completed close path). Two laps made by two different persons or even within the same person will probably be of different shapes. Therefore, the challenge is to have a dynamic way of detecting lapping of different geographical circular shapes. This problem is completely solved by using orientation. No matter what kind of circular shapes a person may lap, the orientation values of a lapping pattern are either linearly increasing or decreasing from the original value of α° to 360° or 0° and then back to α° . To detect these linear trends (or lapping), we use a linear approximation model to check for such trend (α° to 360° or 0° and then back to α°). The boundary values of 0° and 360° are theoretical. In our algorithm, we use the range of $[0^\circ-20^\circ]$ and $[340^\circ-360^\circ]$ in case a person does not make a complete lap. If a lap is determined, we conclude accordingly.

If neither pacing nor lapping nor direct is found, we conclude the pattern as random.

Algorithm 6 Reverse-SAX Based Classification Algorithm

Inputs:

- $O_1, O_2, \dots, O_n (n \in \mathbb{N})$: orientation time-series signal;

Output:

- pattern type ("direct", "random", "lapping", or "pacing")

```

1. apply reverse-SAX representation to  $O_1, O_2, \dots, O_n (n \in \mathbb{N})$ 
2. if major travelled direction exists or travelled time is uniformly distributed
3.     label "direct"
4. else
5.     if least square regression fitting of pacing model is found
6.         label "pacing"
7.     elseif linear model of lapping is found
8.         label "lapping"
9.     else
10.        label "random"
11.    endif
12. endif

```

5.3.2 Results of RSAX in the controlled study

We use the testing data of 14 subjects described in the previous Section of this Chapter and apply the reverse-SAX based algorithm to classify travel patterns. Table 5.6 reports the performance results of the proposed algorithm. a is the number of alphabets used to discretize the orientation signals, which was described in Table 5.4. In general, $a=8$ yields the most dominant classification recall. But, $a=8$ takes the longest classification time. This is understandable because the data are represented in finer granularity when value of a increases.

Table 5.6: Classification Results of Reverse-SAX Based Algorithm

Subjects	a=4		a=6		a=8	
	Recall	Time	Recall	Time	Recall	Time
1	80.36	0.18	82.14	0.26	80.36	0.26
2	69.09	0.11	67.27	0.15	72.73	0.14
3	84.91	0.11	88.68	0.20	90.57	0.18
4	69.35	0.19	74.19	0.22	79.03	0.27
5	66.67	0.04	73.33	0.06	73.33	0.06
6	87.76	0.07	97.96	0.08	95.92	0.11
7	58.00	0.06	70.00	0.07	82.00	0.08
8	63.46	0.10	80.77	0.10	80.77	0.14
9	70.59	0.09	92.16	0.08	86.27	0.11
10	73.08	0.10	82.69	0.10	84.62	0.11
11	100.00	0.03	100.00	0.04	100.00	0.03
12	79.00	0.24	87.00	0.25	89.00	0.31
13	82.00	0.20	90.00	0.15	92.00	0.17
14	77.27	0.06	81.82	0.10	81.82	0.16
Average	75.82	0.11	83.43	0.13	84.89	0.15

Table 5.7 compares the results produced by DTW using one nearest neighbor (1NN) classifier, SAX using 1NN classifier, reverse-SAX using 1NN classifier, and reverse-SAX using the reverse-SAX based algorithm (RSAX). The most prominent classification results of each classifier from Table 5.5 and Table 5.6 are reproduced in Table 5.7. The results show that RSAX outperforms other algorithms in terms of classification recall and classification time. The mean difference of classification recall between RSAX and other algorithms ranges from 6.55% to 25.78%. DTW takes the longest processing time and produces the lowest classification accuracy in general. RSAX is the most efficient classifier and on average it is exponentially faster than other classifiers. Specifically, it is almost 9 times, 51 times, and 739 times faster than DTW, SAX, and reverse-SAX with 1NN classifier. If we take the size of the testing set into account, RSAX takes around 2 milliseconds to classify a single travel pattern while DTW, SAX, and reverse-SAX 1NN classifiers take almost 2000 milliseconds, 1328 milliseconds, and 23 milliseconds respectively.

Table 5.7: Classifiers' Performance

Subjects	Total	DTW_1NN		SAX_1NN (w=32,a=6)		Reverse-SAX_1NN (a=6)		Reverse_SAX_RSAX (a=8)	
		Recall	Time	Recall	Time	Recall	Time	Recall	Time
1	56	53.61	114.27	58.93	8.42	75.00	2.32	80.36	<i>0.26</i>
2	55	53.77	69.00	65.45	8.50	69.09	1.29	72.73	<i>0.14</i>
3	53	58.95	109.24	64.15	8.27	71.70	1.36	90.57	<i>0.18</i>
4	62	63.96	350.15	64.52	10.28	87.10	2.53	79.03	<i>0.27</i>
5	15	53.81	4.70	73.33	0.62	93.33	0.12	73.33	<i>0.06</i>
6	49	67.12	14.57	75.51	6.87	83.67	0.99	95.92	<i>0.11</i>
7	50	64.19	11.66	86.00	6.74	90.00	0.88	82.00	<i>0.08</i>
8	52	68.03	31.53	69.23	6.95	80.77	0.91	80.77	<i>0.14</i>
9	51	69.50	19.95	60.78	7.45	78.43	1.06	86.27	<i>0.11</i>
10	52	75.24	60.27	84.62	6.96	84.62	0.92	84.62	<i>0.11</i>
11	8	57.58	3.31	50.00	0.22	75.00	<i>0.03</i>	100.00	<i>0.03</i>
12	100	54.15	485.18	57.00	27.81	75.00	4.60	89.00	<i>0.31</i>
13	50	45.81	230.59	50.00	6.70	74.00	1.05	92.00	<i>0.17</i>
14	22	41.88	47.37	54.55	1.37	59.09	0.25	81.82	<i>0.16</i>
Average		59.11	110.84	65.29	7.66	78.34	1.31	84.89	0.15

To test whether RSAX has significantly improved the classification performance over SAX and Reverse-SAX with 1NN classifiers, we conduct the 10-fold cross validation on the 14 datasets. DTW is not included due both of its slow processing capability and low sensitivity. Table 5.8 summarizes the average results of each dataset.

Table 5.8: Results from 10-fold cross validation experiments

Subjects	SAX_1NN (w=32,a=6)		Reverse_SAX_1NN (a=6)		Reverse_SAX_RSAX (a=8)	
	Recall	Time	Recall	Time	Recall	Time
1	57.74	19.656	73.40	5.766	76.88	0.546
2	65.82	19.497	70.16	2.796	74.78	0.311
3	60.72	16.538	79.94	2.942	91.15	0.381
4	66.20	23.683	86.95	5.759	79.23	0.632
5	70.71	1.316	74.14	0.265	77.52	0.110
6	70.91	16.165	79.65	2.152	90.90	0.210
7	74.67	15.346	82.59	1.836	81.38	0.182
8	65.70	15.898	73.91	2.028	79.80	0.228
9	67.28	17.115	72.50	2.336	83.66	0.313
10	80.07	16.074	79.43	1.961	86.97	0.239
11	60.19	0.500	70.56	0.076	100.00	0.060
12	60.80	62.657	76.40	10.487	90.20	0.658
13	53.70	15.568	74.86	2.357	89.02	0.380
14	48.01	3.016	65.96	0.553	80.53	0.176
Average	64.47	17.359	75.75	2.951	84.43	0.316

We use the Sign test to test the hypothesis that RSAX improves the classification recall compared to SAX and reverse-SAX with 1NN classifier. The Sign test is recommended for comparing two classifiers on a single domain [126]. We count the number of times that the first classifier outperforms the second classifier, and the number of times that the second classifier outperforms the first one. Ties (both perform equally) cases are excluded. The null hypothesis (stating that the two classifiers perform equally well) holds if the number of wins follows a binomial distribution. Specifically speaking, a classifier should perform better on at least N datasets to be considered statistically significantly better at the α significance level, where N is the critical value for the Sign test at the α significance level. At the one-tail probability of

0.05, all the p-values from Table 5.9, which summarizes the details of the Sign tests, suggest to reject the null hypothesis. There is sufficient evidence at 95% confidence level to conclude that RSAX outperforms other algorithms in terms of classification recall.

In conclusion, the experimental results show that RSAX is significantly better than other algorithms used in the comparison study in terms of classification recall and time. In reality, it is recommended to use RSAX to identify travel patterns due to its efficient processing capability and sensitivity.

Table 5.9: Details of the Sign test to compare the performance of RSAX with other algorithms

	SAX_1NN	Reverse-SAX_1NN
Number of datasets excluding ties	14	14
Number of wins	0	2
p-value	6.10352E-05	0.006469727

5.4 Using RSAX in the Uncontrolled Study

This Section reports the results from our uncontrolled study in which we use RSAX to identify travel patterns of non-dementia and dementia persons.

5.4.1 Method

5.4.1.1 Subjects and Ethical considerations

In total, 21 non-dementia subjects and 2 PWD participated in the study. 14 non-dementia subjects are those who participated in the controlled study reported earlier. Additional 7 senior non-dementia subjects were recruited from the Clementi and Holland Village area in Singapore. Subjects with dementia were recruited from a dementia daycare centre in Singapore. The criterion for inclusion is the subject is capable of independent ambulation without exhibiting strongly antisocial behavior. For dementia subjects, another inclusion criterion is that he/she is at risk of wandering or exhibits wandering behavior. This study was approved by the Institutional Review Board (IRB) of NTU, and the management committee of the care centre. Management personnel at the care centre contacted the eligible subjects' authorized proxies and

explained the purpose, research protocol, and ethical considerations when the proxies visited the care centre. The proxies then provided their written, informed consent. The ethical considerations were as follows: (1) participation in the study was voluntary, (2) any participant could withdraw from the study at any time, and (3) participation status would not affect the treatment or care of the subjects. The descriptive statistics of the 7 additional non-dementia subjects (numbered from 15 to 21) and 2 dementia subjects (numbered as 22 and 23) are presented in Table 5.10.

5.4.1.2 Apparatus

We used a wearable inertial monitor (Opal) from APDM (Inc.) [106] for data collection. We chose APDM monitor because it is among the few inertial sensors available in the market that allow users to access the raw orientation data and it has been used in numerous Parkinson's and other movement disorders studies [106]. The monitor weighs 22 grams with battery and has dimensions of 48.5x36.6x13.5 mm with an internal storage of 8 GB (equivalent to 720 hours of recording). The monitor includes a full suite of triaxial sensors (accelerometer, gyroscope and magnetometer) that measure acceleration, rotational rate, magnetic field strength, temperature, and orientation. The data sampling rate can be 20-128Hz. We found that 20Hz is good enough because the walking direction of an elderly does not change every second.

5.4.1.3 Procedure

The monitor was attached to the subject around the waist during experiments and data collection (Fig. 5.5a). We also explored the feasibility of placing the monitor on the wrist or ankle. A subject was asked to wear the device on the 3 different parts of the body (Fig. 5.5a). For each placement of the device, the subject walked on the same straight path and the data were logged and plotted in Fig. 5.5b. While the data quality was not much affected by the device placement (Fig. 5.5b), non-dementia subjects told us that they felt more comfortable with the monitor belted around their waist. For dementia subjects, device placement seemed to make little difference as they soon forgot about the monitor. The care centre staff advised that putting the monitor around the waist is more secure. Following NTU IRB approval, recruits

were informed that the study would collect their movement using a small lightweight monitor. In this uncontrolled study, each non-dementia subject was free to walk (including pause and stop sometimes) in various patterns on their own in an open area of 15m x 10m for 10 minutes to an hour. For each dementia subject, data collection was done on one single separate morning. We helped the dementia subjects to put on the monitor after their medications and morning tea break and collected it before their afternoon nap. The subjects need to rest and take a nap after their lunch and are picked up by the family members around 3:00 PM; hence, we did not collect data in the afternoon. The total data collection time for each dementia subject was around 30-60 minutes.

To establish the ground truth, we closely followed, observed, and recorded the subjects' movements. We also used voice recordings to record the movements such as walking straight, turn right, pacing, lapping etc. Each walking episode exhibited by the subjects is labelled into the corresponding travel pattern of direct, pacing, lapping, or random based on the subject's movements. The travel patterns were coded according to a protocol guided by gerontologists [37]. This pattern coding procedure continued until the subject finished the experiment. After we loaded all the data into our computer, we used the voice recordings to double check and ensure that all patterns were correctly coded. These baseline results provide the ground truth estimation of the travel patterns which the recruited subjects exhibit. And they will be used to evaluate the accuracy of the developed algorithm subsequently.

Figure 5.5: a) APDM monitor is attached to the wrist, waist and ankle of a recruited subject b) Plotting orientation signals of a direct pattern collected when placing the monitor on the wrist, waist and ankle

5.4.2 Results and Discussion

5.4.2.1 Results

In this uncontrolled study, the subjects wore the APMD device until completion of experiments because there is no mechanism on the device allowing us to collect inertial data only when the subjects were moving. Therefore, the first step prior to classification is to segregate the data into episodes where the subject were walking. This is accomplished by checking if the translational acceleration exceeds an empirical threshold of 0.25 m/s^2 for at least 3 seconds. To exclude cases where the subject jumps up and down at the same spot, we check the Y-axis acceleration component. Once a walking movement is detected, the program will start tracking the movement orientation until it detects the subject has made a complete stop (acceleration falling below the threshold for some time).

Fig. 5.6-5.11 presents the segmentation results of each subject's inertial data into episodes of walking. In these Figures, the horizontal axis represents the data length or the size of the data collected for each subject. By dividing these sampling points by the sampling frequency, we can have the time information. The top graph plots the orientation signal at each sampling point. The middle graph plots the linear acceleration collected and the bottom graph presents the segmented episodes where the values of 1 and 0 indicates the person is walking and not walking respectively. The end sampling point has a value of 2 to indicate the completion of experiment. Each continuous window of 1 in the bottom graph presents an episode of walking whereas each continuous window of 0 presents the subject is not moving.

Figure 5.6: Orientation, Acceleration, and Segmented Episodes of Subjects 1, 2, 3, and 4

Figure 5.7: Orientation, Acceleration, and Segmented Episodes of Subjects 5, 6, 7, and 8

Figure 5.8: Orientation, Acceleration, and Segmented Episodes of Subjects 9, 10, 11, and 12

Figure 5.9: Orientation, Acceleration, and Segmented Episodes of Subjects 13, 14, 15, and 16

Figure 5.10: Orientation, Acceleration, and Segmented Episodes of Subjects 17, 18, 19, 20

Figure 5.11: Orientation, Acceleration, and Segmented Episodes of Subjects 21, 22, and 23

Once the episodes of walking for each subject are identified, we apply RSAX algorithm to the orientation signal in each episode to classify travel patterns. Table 5.10 presents the results of using RSAX to identify travel patterns of 23 recruited subjects. Subjects numbered 22 and 23 are dementia subjects. In Table 5.10, the classification results column lists both the ground truth (the top string in the cell) and the classified patterns (the bottom string in the cell) by RSAX. For example, subject 1 has 8 episodes of direct patterns. RSAX has identified correctly 7 direct patterns. Two direct pattern is misclassified as random. These 2 misclassified episodes by RSAX are underlined, italicized, and not bolded. Bold episodes indicate correct classification. In general, the classification recall is 88.5% and the mean classification time for each episode is 0.0074 seconds. For non-dementia subjects, RSAX is able to correctly identify the travel patterns for at least 75% of the episodes. Perfect classification is obtained for dementia subjects. The full datasets of all 23 subjects and the classification results are presented in the Appendix 2. In the next Section, we will discuss the misclassification results and lessons learnt.

Table 5.10: Classification Results using RSAX on 23 Subjects (D:Direct, P:Pacing, L:Lapping, R:Random)

Subject	Male/ Female	Age	Classification Results	Number of Patterns Identified	Number of Incorrect Classification	Classification Recall (%)	Classification Time (s)
1	M	26	'DDDDDDDD' ' <u>R</u> DD <u>R</u> DDDD'	8	2	75.0	0.0020
2	M	55	'PPPPRPPPP' 'PPPPRPPPP'	9	0	100.0	0.0059
3	F	24	'DLLLLLLL' 'DLLLLLLL'	9	0	100.0	0.0065
4	F	54	'RRRRR' 'RR <u>P</u> RR'	5	1	80.0	0.0045
5	F	24	'RRRR' ' <u>P</u> RRR'	4	1	75.0	0.0066
6	F	24	'DDPLRPLR' ' <u>R</u> RRL <u>P</u> PLR'	8	4	50.0	0.0141
7	M	22	'DDPLRDPRL' 'DDPL <u>P</u> DPRL'	9	1	88.9	0.0052
8	M	59	'DDDPRLPLR' 'DDDP <u>P</u> LPLR'	9	1	88.9	0.0062
9	F	53	'DDPPLLRR' 'DDPPLLRR'	8	0	100.0	0.0071
10	M	24	'DDPPLLRR' 'DDPPLLRR'	8	0	100.0	0.0051
11	M	55	'DDDPPLLRR' 'DDD <u>L</u> PPLLRR'	9	1	88.9	0.0044
12	M	30	'DDPPLLRR' 'DDPPLL <u>R</u> '	8	1	87.5	0.0060
13	M	35	'DDPPLLRR' 'DDPPLLRR'	8	0	100.0	0.0053
14	M	54	'DDPPLLRR' 'D <u>R</u> PPLL <u>R</u> '	8	2	75.0	0.0054
15	F	53	'DDPPLLRR' 'DDPPLLRR'	8	0	100.0	0.0054
16	F	62	'DPLLRRDD' 'DRLLRRDD'	8	0	100.0	0.0058
17	M	69	'DDPPLLRR' 'DD <u>R</u> LLRR'	8	2	75.0	0.0081
18	M	74	'DDPPLLRR' 'DDP <u>P</u> LLRR'	8	1	87.5	0.0060
19	F	72	'DDPPLLRR' 'DDPPLL <u>P</u> '	8	2	75.0	0.0060
20	F	63	'DDPPLLRRD' 'DDPPLL <u>R</u> D'	9	1	88.9	0.0078
21	M	69	'DDPPLLRR' 'DDPPLLRR'	8	0	100.0	0.0087
22	M	68	'LRDDRDD' 'LRDDRDD'	7	0	100.0	0.0162
23	F	63	'RPRDD' 'RPRDD'	5	0	100.0	0.0215
Average		49.2 ± 18.4				88.5	0.0074

5.4.2.2 Discussion

Figures 5.12 and 5.13 present the misclassification cases in Table 5.10. In total, 5 direct patterns are misclassified as random. 5 pacing patterns are misclassified as lapping and random. 10 random patterns are misclassified as pacing and lapping. There is no misclassification for lapping patterns. In Figures 5.12 and 5.13, the original orientation signals are represented by red circles (o) and the quantized signals using reverse-SAX representation are marked with green cross (x) signs. The vertical axis represents the orientation values and the horizontal axis represents the data points in each episode. For each graph, the subject, the pattern number (the order of the pattern in the ground truth estimation which is reported in Table 5.10), the classified pattern by RSAX are summarized in the graph title.

Figure 5.12: Misclassification of direct patterns

Fig. 5.12 shows that RSAX failed to detect direct patterns in the first 4 cases (subjects 1 and 6) due to the boundary values. In these cases, it can be seen that the subjects were walking in the north direction close to 360° or 0° . RSAX is not able to recognize this special case and perceives that the person was walking in 2 different directions. Hence, RSAX identifies these as random. In the case of subject 14, the major travel direction condition is not satisfied (70% of the time), and there are 3 travel directions in which the time distribution is not uniform; therefore, this is not considered as direct by RSAX.

Figure 5.13: Misclassification of pacing patterns

Fig. 5.13 shows that RSAX algorithm cannot find a fitting model for those pacing patterns. The reason is similar to the misclassification of direct patterns in Fig. 5.12 due to boundary values. In these cases, we can notice that the subjects were traveling in the direction of 180° or the magnetic south direction. When the subjects made 180° turns, the azimuth values fluctuate around the boundary values of 0° and 360° which is the direction of magnetic north. In the cases of subjects 6, 17 (pattern numbered 3), 18, the subjects did not make a sharp 180° turn. Instead, they took some time to make the turns. Therefore, RSAX maps these patterns to random. In the cases of subjects 11 and 17 (pattern numbered 4), 2 consecutive 180° turns made by the subjects accidentally made it a full 360° turn (due to boundary values) and hence, the algorithm detects those cases as lapping.

Figure 5.14: Misclassification of random patterns

Fig. 5.14 presents cases whereby random patterns were mapped to pacing and lapping. For subjects 4, 5, 6, 7, 19 (patterned number 8), RSAX found a fit for pacing as shown in the black dash circles in the graphs. However, the turns made in these cases are probably more than 180° . Therefore, practically these should not be labeled as pacing. Hence, the parameters of the fitting model for pacing need to be further fine-tuned. For subject 8, the pacing is not clearly seen from the graph. For subjects 12, 14, 19 (pattern numbered 7), 20, there exist some circular movements made by the subjects, which is shown by the some segments where the orientation linearly increases from 0° to 359° or decreases from 359° to 0° . Hence, the classifier straightly maps those as lapping.

Table 5.10 also presents the classification results of dementia subjects. Subject 22 has moderately severe dementia and subject 23 has moderate dementia. Subject 22 is a wanderer whereas subject 23 is not but has difficulty in traveling (e.g. disoriented while traveling from care centre back home and even get lost once) at times. Subject 22 likes to go outdoors. Therefore, his data were collected while he was walking outdoors under our close surveillance. On the contrary, subject 23 prefers doing indoor activities with other dementia subjects; hence, her data were collected indoors. The total data collection time for subject

22 and subject 23 was 62 and 34 minutes respectively. However, the subjects spent majority of the time to participate in the activities at the care centre or sitting down to have coffee after a short walk. The RSAX algorithm was able to detect all the patterns correctly for both subjects. We have made 3 key observations. First, random patterns in an outdoor setting can cover large areas and are combinations of consecutive direct-pattern segments. In one particular episode, the subject walked randomly around a residential estate of 120m x 150m to look for his home. Second, pacing could be a form of good exercise that the subject is aware of. Subject 23 told us that she usually walks up and down to exercise because she believes it is good for her health. Third, both subjects wandered during mid-morning (9:45AM to 11:00AM) and especially before lunch time. During this period, the subjects are free to do things on their own if they do not engage in entertainment or group activities. In the early morning or during lunch time, the subjects will be eating, taking medicines, or doing routine rehabilitation exercises. These prescribed activities keep them busy and distract them from wandering.

Chapter 6 Summary and Conclusions

This chapter summarizes the work done and discusses directions for future works

6.1 Summary

In the initial stages of our research, we first justify the need and motivation for managing wandering behavior of PWD. We then present the conceptual map of wandering science serving as a guideline and reference for technologists who are interested in building technologies for wandering management. In addition, we propose a systematic framework identifying future wandering management applications that can be developed or further enhanced. We perform an extensive literature survey of existing technological works that address these 4 domains in the 5Ws1H conceptual map: WHAT-WHERE-WHY-HOW. In particular, we explore sensors to geo-fence and prevent elopement, devices to track and locate PWD who wander, information services to assist caregivers, tools to measure dimensions of dementia-related wandering, and tools that analyze proximal factors as well as study background factors. Based on this review, we further discuss research and design issues, human factors, ethics, security and privacy that need to be considered when implementing applications for wandering management. This gives a clear view of the state of the art, and the direction for the focus of our research.

By assessing the need of gerontologists and researchers in dementia-related wandering, we have developed algorithms for automated classification of wandering patterns of PWD. The algorithms are formulated based on a psychologically justified conceptual Martino-Saltzman typology. We propose two automated approaches for classifying travel patterns of nursing home residents with various stages of dementia. In the machine learning approach, eight different classifiers NB, MLP, LB, C4.5, RF, BAG, k-NN, and SVM are employed. The methodology is evaluated on movement data produced by RFID tags placed on the subjects' body. The subjects in this study are five PWD who have similar age distribution and suffer

from wandering. The travel patterns including wandering are manually labeled so as to have a ground truth of classification. The results are expressed in terms of sensitivity, specificity, precision, recall, F1-measure and latency. The sensitivity, specificity, precision, recall, F1-measure, and latency of the RF classification algorithm were 92.3%, 92.3%, 92.2%, 92.3%, 92.2%, 0.03s respectively. In the deterministic approach, we also introduce a predefined tree-based algorithm that improves the classification accuracy by 5.9% to 98.2% and significantly reduces the classification latency to 0.0003s. The deterministic algorithm offers several advantages: (1) it is not based on thresholds, (2) it is based on an operationalized (clearly distinguishable and measurable through empirical observations) definition of wandering, (3) the classification process is formed from a logically deduced state diagram depicting transformations of travel patterns which is agreeable with the empirical results achieved by classical machine learning algorithms, (4) the classification latency is very small, which enables the algorithm to be deployed in real-time and mobile applications aiming to detect wandering behavior of PWD as soon as it takes place. Additionally, we have also showcased a working prototype of the algorithm on a mobile device and demonstrated that the method could be feasibly developed into a practical service for dementia care.

Experience gained from deploying the mobile health application motivates us in using available inertial sensors on mobile devices to identify travel patterns so as to reduce the high cost incurred of localization systems. In the controlled study, we use orientation signals from a smart phone device to classify travel patterns of 14 non-dementia subjects. We introduce the reverse-SAX representation of time-series orientation signals. Using the same 1-NN classifier, the new representation has showed advantages in terms of classification recall and classification time. The average recall is significantly improved by 13.05% and 19.05% and the classification time is reduced from 6 times to 84 times as compared to SAX and DTW respectively. In addition, we present a new classifier (RSAX) which is based on reverse-SAX representation and the logic of the predefined tree-based algorithm. The RSAX classifier is superior to all algorithms being compared. It achieves an average classification recall of 84.89% which is 6.52%, 19.6% and 25.78% better

than reverse-SAX, SAX and DTW using 1-NN classifier. RSAX is significantly efficient in identifying travel patterns. On average, it takes 0.15 seconds to classify the whole test datasets, which is 9 times, 51 times and 739 times faster than reverse-SAX, SAX, and DTW 1-NN classifier.

We also carry out the uncontrolled study on total 23 subjects, 2 of whom is dementia. The RSAX classifier achieves 88.5% of classification recall on average. It achieves perfect classification results on dementia subjects and in identifying lapping patterns. And it takes approximately 7.4 milliseconds to classify a travel episode. This shows that RSAX is suitable for real-time applications aiming to detect wandering patterns of PWD as soon as it occurs.

6.2 Limitations

The predefined tree-based algorithm has several limitations: (1) it was tested on datasets of five PWD, (2) the movement data are confined by physical rooms and indoor settings. In reality, a subject can wander within a large area such as a function hall or wander outside the care environments, (3) the algorithm has some shortcomings in the recognition of travel patterns with complicated and varied geometrical forms. Contextual information and geographical information such as the map, layout or design of the monitored area can be incorporated to refine the classification algorithm.

The RSAX classifier shows disadvantages in classifying direct and pacing patterns when the subject is moving in the magnetic north direction or when the orientation values fluctuate around that direction. In addition, using temporal information and its distribution to detect direct patterns need to cater for cases when the threshold value does not meet. RSAX also shows its deficiency in detecting random patterns that combine a mix of lapping and pacing patterns. The parameters of the fitting model for pacing need to be fine-tuned to so that it could reduce the misclassification rate when the subjects make a long 180° turns or turn at a bigger or smaller angle than the 180° .

6.3 Suggestions and Recommendations for Future Research

Several directions are envisioned for future work with the developed algorithms and their applications to dementia wandering research. These prospective topics of research are detailed below.

6.3.1 *Large scale evaluation of the predefined tree-based algorithms*

In the future, more evaluation should be made to validate the performance of the predefined tree-based algorithms on large data samples. Actual wandering data from PWD is the best and clinically significant data. However, expensive resources and intensive manpower are required to collect this source of data. One suggestion is to recruit volunteers to act as wanderers so as to collect extra data for study. Though the data are not of actual PWD, it is probably the second best we can have in the near future. In addition, it is recommended to test the applicability of the proposed deterministic algorithm with finer location data resolution (e.g. 3-D space coordinates). In order for the proposed logic to work well with finer location data, we suggest to cluster nearby data points (coordinates) together and partition the coordinates location sequences (or trajectories) into sequences of coarse characteristic locations (e.g. areas of 2mx2m). Such tasks can be done by applying the minimum description length principle and density-based spatial clustering of line segments. Then we can apply the proposed logic in the deterministic algorithm to do the classification. We hope to achieve classification results as good as those reported in this pilot study. Another direction is to scale up the deterministic algorithm as the sample size increases by exploring relevant data mining methods geared specifically towards recognizing sequences whose length is not pre-fixed and that have sub-patterns embedded within them such as hidden Markov models or probabilistic suffix trees.

6.3.2 *Enhancement of the RSAX algorithm and large scale evaluation*

Additionally, there are a few suggestions to further enhance the performance of RSAX. First, RSAX uses a simple thresholding technique to detect the major travelled direction and it shows the deficiency when

the criteria do not meet. Exploration of other techniques such as Principal Component Analysis could result in better detection of the major travelled direction from the orientation signals. Second, situations where the person walks in the magnetic north direction should be carefully handled to avoid misclassification. Median filters could be used to handle the cases of the boundary values of 0° and 360° . By looking at the nearby neighbors' values, we can determine whether or not the current value is representative of its surroundings and replace it with the median of those values. Third, the fitting model for pacing should be improved to handle cases where persons make asymmetric 180° turns in a pacing movement. Last, the current classifier simply considers an episode which is neither direct nor pacing nor lapping as random. We suggest to extend the current capability of RSAX in order to differentiate direct and random episodes that comprises a number of straight walks and to recognize random patterns in episodes that have a mix of patterns. Measures such as Fractal D, directed movement, straightness index, or entropy in information theory can be explored in future research. In order to apply these measures, we can transform the acceleration and orientation data to obtain the walking trajectories of the persons. This could be achieved by taking integrals over time based on the sampling rate information. Integration of acceleration will give velocity. Based on the sampling rate and velocity, the distance travelled between 2 points can be calculated. With the orientation information and the distance travelled, one can approximate the X-Y coordinates of the path. Fractal D [127] quantifies spatial variability of animal movements along a continuum from extremely random to highly goal-directed movements. High Fractal D values may occur when changes in path direction are necessary to circumnavigate environmental barriers. Therefore, using these measures could probably help in quantify random patterns and then differentiate it from direct and other patterns.

The developed algorithms were tested on actual PWD. However, the evaluation was limited to 2 dementia subjects. Further evaluation of the algorithms in a large scale study and settings (e.g. nursing homes,

homes of the PWD) should be conducted. In addition, feedbacks from caregivers and physicians should be collected so that the practicality of the algorithms can be assessed and improved.

6.3.3 Domains of application

The algorithms to automatically classify wandering patterns can be used for future studies and applications of dementia wandering. In general, the patterns classified by the algorithms provide clues for researchers and clinicians to construe important aspects of wandering, determine troubling types or amount of wandering, develop and test potentially fruitful interventions for each group of wanderers. Future applications and prospective studies of the automated algorithms are elaborated below.

6.3.3.1 Application to automatically detect and document wandering patterns

In clinical and long-term care settings, wandering is traditionally detected by having human observers to observe PWD and document the wandering patterns including pacing, lapping, and random. Such observational method requires labor and time, and lacks objectivity due to the unpredictable nature of the behavior and due to the fact that during short observation period (usually 20 minutes), PWD may appear very well and may not exhibit any wandering behavior. Another real issue with direct observation method is direct care staff are not professionally trained and too hard pressed for time to observe and document wandering patterns of PWD. Therefore, it is beneficial to both caregivers and dementia-related wandering researchers to apply the automated algorithms such as RSAX to detect and document wandering patterns in real time or offline. With the advancement of smart personal devices such as mobile phones, APDM monitors, Apple watches, it is cost-effective, scalable, and labor-free to install an application to capture orientation signals and analyze the patterns exhibited using the developed algorithms. This solution will help alleviate issues imposed by direct observation method.

6.3.3.2 Application to improve care to wanderers

Previous studies [70, 79] indicated that factors such as emotional, physical needs, pain, or hunger are pertinent to wandering and these can be predictors for pacing and lapping. In fact, pacing is usually triggered because the person is emotionally unsettled, not happy, or something bothering him/her. Thus, there is a clinical benefit to distinguish pacing so that care can be given to the underlying issues. In addition, if a person keeps turning around unnecessarily, it is important for a caregiver to know why so as to offer immediate assistance if needed. Nevertheless, these patterns tend to be short in distance and time and could be easily overlooked by caregivers due to their busy schedule. Therefore, the automated algorithms to identify pacing and lapping can be developed into a real time mobile application that triggers caregivers when PWD exhibit these patterns. Based on these alerts, care staff can pay more attention to the wanderers to find out triggers of their wandering so as to offer timely assistance. In addition, they can inform family caregivers and discover other possible triggers when the wanderers are being taken care of at home. Timely alerts will enable both family and professional caregivers to offer immediate interventions to tackle triggers of wandering and consequently improve the quality of care for PWD.

6.3.3.3 Application to classify types of wanderers

There are three types of wanderers: classic, moderate, and sub-clinical [97]. These types can be classified from 21 computable wandering parameters such as wandering duration, rate, and time of day. Therefore, by using the automated algorithms, it is possible to extract these parameters so as to identify the types of wanderers. A limitation from the previous study [97] is they were unable to collect wandering parameters during nighttime because they used direct observation method to extract wandering patterns and there were not enough labor to observe PWD during nighttime. This issue can be overcome by the proposed solution of using wearable devices to capture orientation signals to detect wandering patterns.

Compared to non-wanderers, classic wanderers tend to be more cognitive impaired, have more severe heart problems, and have slightly less problems with gastrointestinal tract. For moderate wanderers, they

have better gastrointestinal health and better mobility than non-wanderers and a similar level of cognitive impairment. For sub-clinical wanderers, they have less cognitive impairment, better mobility, and poorer health than non-wanderers. Hence, in long term care settings, it would be good to identify these types of wanderers early because early recognition can lead to early intervention of underlying conditions (e.g. gastrointestinal health) each type of wanderers may have.

6.3.3.4 Application for long term care and research on dementia-related wandering

One of the long term care applications is to observe wandering patterns over long period of time to monitor cognitive progression in PWD. Previous studies [2, 23, 108] found that there is a correlation of wandering and cognitive impairment. In fact, increasing amounts of random-pattern wandering (the frequency and overall proportion of time spent) is clearly linked to increased levels of global cognitive impairment. Meanwhile, lapping patterns are less clearly associated with cognitive decline. However, frequent lapping may signify a deteriorating ability to way-finding in PWD [70]. Pacing is not associated with levels of cognitive impairment; however it is more indicative of agitation and anxiety. Therefore, in the long term care settings, the developed algorithms can be further developed to use as a software tool that can provide physicians and researchers the wandering patterns profile or summary of PWD or people with non-dementia. Long term observation of wandering profiles can be an additional and useful channel for physicians and researchers to early detect changes to the person's cognition. Early detection of wandering will allow early treatment and potentially slow down the onset of dementia.

In addition, the developed algorithms may be used to assist gerontologists and researchers to uncover other dimensions of wandering. They can be used to answer the research question on whether lapping or pacing patterns correlate to the Mini Mental State Examination (MMSE) scores. Kearns et al. [127] uncovered the correlation between random movements and MMSE score and found that fractal dimension (a measure of randomness in 14 assisted living facility (ALF) residents' movement paths continuously recorded over 30 days using ultra-wideband sensors) was significantly higher in persons with

lower MMSE scores signifying cognitive impairment. In a subsequent study of 28 subjects [128] recorded over one month replicated the findings of Kearns [127] and found that the randomness of the paths taken by elderly ALF residents reliably differentiated PWD from those without the disorder.

Other empirical typologies [19-20, 76, 78, 79, 80, 83, 97] found that parametric characteristics of wandering behavior including variations in walking speed, the percentage of time involving locomotion, the number of changes in direction among successive movement paths, rate and duration of wandering episodes are useful indicators of a person's changes in cognitive function. Therefore, the personalization of PWD's intervention and close observation of the impact of every intervention to the patient's clinical condition is a crucial step for planning a successful treatment strategy. We hope that advance in further research will result in an automated monitoring system that can measure wandering rates, durations and patterns in order to provide early detection of physical and mental changes of PWD. Such an automated system will enable caregivers to arrange better care distributions, treatments and timely interventions for PWD.

List of Publications

- [1] N.K. Vuong, S. Chan, C.T. Lau, P.L. Yap, A.S. Chen, "*Preliminary Results of Using Inertial Sensors to Detect Dementia-Related Wandering Patterns*," IEEE Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2015, Italy
- [2] N.K. Vuong, S. Chan, C.T. Lau, "*mHealth Sensors, Techniques, and Applications for managing wandering behavior of people with dementia: a Review*," Mobile Health, 11-42, Springer International Publishing, 2014
- [3] N.K. Vuong, S. Chan, C.T. Lau, "*Automated Detection of Wandering Patterns in People with Dementia*," Gerontechnology;12(3):127-147
- [4] N.K. Vuong, S. Chan, C.T. Lau, "*Conceptual Map and Technological Framework to Manage Dementia Wandering*," IEEE International Symposium on Bioelectronics and Bioinformatics (ISBB), 2014, Taiwan
- [5] N.K. Vuong, S. Chan, C.T. Lau, "*An Application of Machine Learning to Classify Dementia Wandering Patterns*," Gerontechnology;13(2):294
- [6] N.K. Vuong, S.G.A. Goh, S. Chan, C.T. Lau, "*A Mobile-Health Application to Detect Wandering Patterns of Elderly People in Home Environment*," IEEE Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2013, Japan
- [7] N.K. Vuong, S. Chan, C.T. Lau, "*Feasibility Study of a Real-Time Wandering Detection Algorithm for Dementia Patients*," Proceedings of the First ACM MobiHoc Workshop on Pervasive Wireless Healthcare, 2011, France

References

- [1] North American Nursing Diagnosis Association. Nursing diagnoses: Definitions & classification (4th ed.). Philadelphia, PA: Nursecom, Inc.
- [2] C.K.Y. Lai and D.G. Arthur, "Wandering behavior in people with dementia," *Journal of Advanced Nursing (J Adv Nurs)*, 2003;44:173-182.
- [3] M. Cesari, et al., "Prevalence and risk factors for falls in an older community-dwelling population," *Journal of Gerontology Series A: Biological Sciences and Medical Sciences*, 2002;57:722-726.
- [4] C.S. Colon-Emeric, D.P. Biggs, A.P. Schenck, K.W. Lyles, "Risk factors for hip fracture in skilled nursing facilities: Who should be evaluated?" *Osteoporosis International*, 2003;14:484-489.
- [5] S. Hirst and B. Metcalf, "Whys and whats of wandering," *Geriatric Nursing*, 1989;5:237-238.
- [6] R. McShane, et al., "Getting lost in dementia: A longitudinal study of a behavioral symptom," *International Psychogeriatrics*, 1998;10:253-260.
- [7] M.A. Rowe and J.C. Glover, "Antecedents, descriptions, and consequences of wandering in cognitively-impaired adults and the safe return (SR) program," *American Journal of Alzheimer's Disease and other Dementias*, 2001;16:344-352.
- [8] J. Rodriguez, "Resident falls and elopement: cost and controls," *Nursing Homes*, 1993;4:16-17.
- [9] H. Nygaard, "Consumption of psychotropic drugs in elderly persons registered at the home nursing center in Bergen, Norway," *International Journal of Geriatric Psychiatry*, 1992;7:53-58.

- [10]C. Siders, et al., "Evidence for implementing nonpharmacological interventions for wandering," *Rehabilitation Nursing*, 2004;29:195-206.
- [11]A. Wimo, M. Prince, "World Alzheimer Report 2010: The global economic impact of dementia," *Alzheimer's Disease International*, 2010.
- [12]A. Wimo, B. Winblad, L. Jonsson, "The worldwide societal costs of dementia: estimates for 2009," *Alzheimer's & Dementia*, 2010;6:98-103.
- [13]L.M. Angiullo, "Wandering behavior in people with dementia. PhD thesis, University of Massachusetts, 1997.
- [14]Profiling the the dementia family carer in Singapore.
<http://www.alz.org.sg/sites/alz.org.sg/files/Profiling%20the%20Dementia%20Family%20Carer%20in%20Singapore%20-%20Executive%20Summary.pdf>
- [15]I.H.G.B. Ramakers, et al., "Symptoms of preclinical dementia in general practice up to five years before dementia diagnosis," *Dementia & Geriatric Cognitive Disorders*, 2007;24:300-306.
- [16]T. Hope, et al., "Wandering in dementia: A longitudinal study," *International Psychogeriatrics*, 2001;13:137-147.
- [17]J. Verghese, et al., "Abnormality of gait as a predictor of non-Alzheimer's dementia," *New England Journal of Medicine*, 2002;347:1761-1768.
- [18]E. Scherder, et al., "Gait in ageing and associated dementias; its relationship with cognition," *Neurosci Biobehav Rev*, 2007;31:485-497.
- [19]T.L. Hayes, M. Pavel, J.A. Kaye, "An unobtrusive in-home monitoring system for detection of key motor changes preceding cognitive decline," *26th IEEE Conference on Engineering in Medicine and Biology*, 2004;4:2480-2483.

- [20]M. Pavel, T.L. Hayes, A. Adami, H. Jimison, J. Kaye, "Unobtrusive assessment of mobility," 28th IEEE Conference on Engineering in Medicine and Biology, 2006;1:6277-6280.
- [21]J. Verghese, R. Holtzer, R.B. Lipton, C. Wang, "Quantitative gait markers and incident fall risk in older adults," Journals of Gerontology Series A: Biological and Medical Sciences, 2009;64A:896-901.
- [22]N. Giladi, T. Herman, I.I. Reider-Groswasser, T. Gurevich, J. Hausdorff, "Clinical characteristics of elderly patients with a cautious gait of unknown origin," J Neurol, 2005;252:300-306.
- [23]D.L. Algase, C.B. Beel-Bates, E.R.A. Beattie, "Wandering in long-term care," Annals of Long-Term Care: Clinical Care and Aging 2003;11:33-39
- [24]K.J. Kim, M.M. Hassan, S. Na, E.N. Huh, "Dementia wandering detection and activity recognition algorithm using tri-axial accelerometer sensors," Proceedings of the 4th IEEE ICUT'09, Fukuoka, 2009.
- [25]F. Miskelly, "Electronic tracking of patients with dementia and wandering using mobile phone technology," Age Aging, 2005;34(5):497-499.
- [26]D.J. Patterson, et al. "Opportunity knocks: a system to provide cognitive assistance with transportation systems," UbiComp2004, LNCS 3205, pp. 433-450.
- [27]D.L. Algase, D.H. Moore, D. Gavin-Dreschnack, C. VandeWeerd. "Wandering definitions and terms" Evidence-based protocols for managing wandering behaviors. Ed. Audrey Nelson & Donna Algase. New York, NY: Springer, 2007. 3-18.
- [28]EmFinders, "Emfinder," www.emfinders.com/
- [29]Aetrex, "GPS Shoe," www.aetrex.com/aetrex-gps-shoe/, 2011
- [30]Lifeline 4000+, <http://www.tunstall.co.uk/Our-products/Telecare-solutions/>

- [31] W.D. Kearns, D. Algase, D.H. Moore, S. Ahmed, "Ultra wideband radio: A novel method for measuring wandering in persons with dementia," *Gerontechnology*, 2008;7(1):48-57.
- [32] D.J. Patterson, et al. "Opportunity knocks: a system to provide cognitive assistance with transportation systems," *UbiComp 2004*, LNCS 3205, pp. 433-450.
- [33] C.C. Lin, et al. "A wireless healthcare service system for elderly with dementia," *IEEE Trans. Info. Tech. Biomed.*, 2006, 10(4):696-704.
- [34] C.C. Lin, et al. "A healthcare integration system for disease assessment and safety monitoring of dementia patients," *IEEE Trans. Info. Tech. Biomed.*, 2008, 12(5):579-586.
- [35] Y.J. Chang, H.H. Liu, T.Y. Wang, "Mobile social networks as quality of life technology for people with severe mental illness," *IEEE Wireless Com.*, 2009, 16(3):34-40.
- [36] J. Peatfield, M. Futurell, C. Cox, "Wandering. An integrative review," *J Gerontol Nurs*, 2002;28:44-50.
- [37] D.L. Algase, H.D. Moore, C. Vandeweerd, D.J. Gavin-Dreschnack, "Mapping the maze of terms and definitions in dementia-related wandering," *Aging Ment Health*, 2007;11:686-698.
- [38] M. Halek and S. Bartholomeyczik, "Description of the behavior of wandering in people with dementia living in nursing homes – a review of the literature," *Scandinavian Journal of Caring Sciences*, 2011;
- [39] North American Nursing Diagnosis Association (NANDA). *Nursing diagnosis: definitions and classification*, 2001-2002 (pp. 206-207). Philadelphia, PA: Author.

- [40] E.R.A. Beattie and L.M. Struble, "Evidence-based practice protocols for wandering," Evidence-based protocols for managing wandering behaviors. Ed. Audrey Nelson & Donna Algate. New York, NY: Springer, 2007. 337-352.
- [41] Department of Veterans Affairs, Veterans Health Administration. Management of wandering and missing patient events. VHA DIRECTIVE 2002-013, March 4, 2002.
- [42] D.L. Algate, D.H. Moore, D. Gavin-Dreschnack, C. VandeWeerd. "Wandering definitions and terms" Evidence-based protocols for managing wandering behaviors. Ed. Audrey Nelson & Donna Algate. New York, NY: Springer, 2007. 3-18.
- [43] D.L. Algate, H.D. Moore, C. Vandeweerd, D.J. Gavin-Dreschnack, "Mapping the maze of terms and definitions in dementia-related wandering," Aging Ment Health, 2007;11:686-698.
- [44] D.L. Algate, L. Yao, C.A. Beel-Bates, J. Song. "Theoretical models of wandering" Evidence-based protocols for managing wandering behaviors. Ed. Audrey Nelson & Donna Algate. New York, NY: Springer, 2007. 19-52.
- [45] D.L. Algate. "Assessment of wandering behaviors" Evidence-based protocols for managing wandering behaviors. Ed. Audrey Nelson & Donna Algate. New York, NY: Springer, 2007. 75-102.
- [46] B.R. Connell and M.P. Calkins. "Environmental design" Evidence-based protocols for managing wandering behaviors. Ed. Audrey Nelson & Donna Algate. New York, NY: Springer, 2007. 299-336.
- [47] B. Hodgkinson, S. Koch, R. Nay, M. Lewis, "Managing the wandering behavior of people living in a residential aged care facility," Int J Evid Based Healthc, 2007;5:406-436.
- [48] G. Stokes. Wandering – Common problems with the elderly confused. Ed. Una P Holden. Oxon England, Winslow Press, 1988. 35

- [49] D. H. Moore, D.L. Algase, G. Powell-Cope, S. Applegarth, E.R.A. Beattie, "A framework for managing wandering and preventing elopement," *American Journal of Alzheimer's Disease & Other Dementia*, 2009;24(3):208-219.
- [50] William D. Kearns and James L. Fozard. "Technologies to manage wandering" Evidence-based protocols for managing wandering behaviors. Ed. Audrey Nelson & Donna Algase. New York, NY: Springer, 2007. 277-298.
- [51] S.C. Castle and M.K. Rutledge. "Pharmacological interventions associated with wandering" Evidence-based protocols for managing wandering behaviors. Ed. Audrey Nelson & Donna Algase. New York, NY: Springer, 2007. 215-250.
- [52] F.G. Miskelly, "Assistive technology in elderly care," *Age and Ageing*, 2001;30:455-458.
- [53] F. Meiland, et al. "COGKNOW: Development of an ICT device to support people with dementia," *The Journal on Info. Tech. in Healthcare*, 2007;5(5):324-334.
- [54] A.J. Bharucha, et al. "Intelligent assistive technology applications to dementia care: current challenges, limitations, and future challenges," *AM J GeriatrPsychiat*, 2009;17(2):84-104.
- [55] C. Phua, et al., "State-of-the-Art assistive technology for people with dementia," *Handbook of Research on Ambient Intelligent & Smart Environments: Trends & Perspectives*, 2011, pp. 300-319.
- [56] P. Rashidi and A. Mihailidis, "A survey on ambient assisted living tools for older adults," *IEEE Transactions on Information Technology in Biomedicine*, 2012;17(3):579-590.
- [57] W.D. Kearns, D. Rosenberg, L. West, S. Applegarth, "Attitudes and expectations of technologies to manage wandering behavior in persons with dementia," *Gerontechnology*, 2007;6(2):89-101.

- [58]D. Chen, A.J. Bharucha, H.D. Wactlar, "Intelligent video monitoring to improve safety of older persons," 29th EMBS Conference, 2007:3814-3817, New York, USA.
- [59]M. Chan, S. Bonhomme, D. Esteve, E. Campo, "Individual movement trajectories in smart homes," 2008, ICBME, 1014-1018.
- [60]D.M. Taub, et al. "The Escort system: a safety monitor for people living with Alzheimer's disease," IEEE Pervasive Computing, 2011;10(2):68-77.
- [61]F. Hanser, A. Gruenerbl, C. Rodegast, P. Lukowicz, "Design and real life deployment of a pervasive monitoring system for dementia patients," 2nd International Conference on Pervasive Computing Technologies for Healthcare, 2008.
- [62]M. Rowe, S. Lane, C. Phipps, "CareWatch: a home monitoring system for use in homes of persons with cognitive impairment," Top GeriatrRehabil, 2007;23:3-8.
- [63]D. Chen, A.J. Bharucha, H.D. Wactlar, "Intelligent video monitoring to improve safety of older persons," 29th EMBS Conference, 2007:3814-3817, New York, USA.
- [64]Digital Angel, Inc.: www.digitalangel.com
- [65]K. Shimizu, K. Kawamura, K. Yamamoto, "Location system for dementia wandering," 22ndIEEE EMBS, 2000, 1556-1559.
- [66]H. Ogawa, Y. Yonezawa, H. Maki, H. Sato, W.M. Caldwell, "A mobile phone-based safety support system for wandering elderly persons," 26thIEEE EMBS, 2004, 3316-3317.
- [67]F. Miskelly, "A novel system of electronic tagging in patients with dementia and wandering," Age Aging, 2004;33:304-306.
- [68]N. Ashida, et al., "A monitoring of wandering behavioral pattern of senile dementia with IC tag," 3rd APT Telemedicine Conference, 2005:80-84.

- [69]C. Greiner, K. Makimoto, M. Suzuki, M. Yamakawa, N. Ashida, "Feasibility study of the integrated circuit tag monitoring system for dementia residents in Japan," AM J Alzheimer's Dis, 2007;22(2):129-136.
- [70]K. Makimoto, M. Yamakawa, N. Ashida, Y. Kang, K.R. Shin, "Japan-Korea joint project on monitoring people with dementia," World Congress on the Internet and Medicine, 2006.
- [71]A. Almudevar, A. Leibovici, A. Tentler, "Home monitoring using wearable radio frequency transmitters," ArtifIntell Med, 2008;42:109-120.
- [72]W.D. Kearns and J.L. Fozard, "Ultra-wideband radio assessment of locomotion in elderly," Gerontechnology, 2008;7(2):138.
- [73]J. Helmy, A. Helmy, "The Alzimio app for dementia, autism & Alzheimer's: using novel activity recognition algorithms and geofencing," IEEE International Conference on Smart Computing, 18-20 May 2016
- [74]P.A. Moreno, M.E. Hernando, E.J. Gomez, "Design and technical evaluation of an enhanced location-awareness service enabler for spatial disorientation management of elderly with mild cognitive impairment," IEEE Journal of Biomedical and Health Informatics, 2015;19(1):37-43
- [75]J. Wan, C.A. Byrne, M.J. O'Grady, G.M.P. O'Hare, "Managing wandering risk in people with dementia," IEEE Transactions on Human-Machine Systems, 2015;45(6):819-823
- [76]D.L. Agase, E.R.A. Beattie, S.A. Leitsch, C.A. Beel-Bates, "Biomechanical activity devices to index wandering behaviour in dementia," AM J Alzheimer's Dis and Other Dementias, 2003;18(2):85-92.

- [77]K. Makimoto, et al. "Temporal patterns of movements in institutionalized elderly with dementia during 12 consecutive days of observation in Seoul, Korea," *AM J Alzheimer's Dis*, 2008;23(2):203-206.
- [78]D.L. Algase, C.L. Antonakos, E. Beattie, C.A. Beel-Bates, L. Yao, "New parameters for daytime wandering," *Res GerontolNurs*, 2009;2(1):58-68.
- [79]A. Nakaoka, et al. "Pacing and lapping movements among institutionalized patients with dementia," *AM J Alzheimer's Dis*, 2010;25(2):167-172.
- [80]W.D. Kearns, V.O. Nams, J.L. Fozard, "Tortuosity in movement paths is related to cognitive impairment. Wireless fractal estimation in assisted living facility residents," *Methods of Information in Medicine*,2010;49: 592-598.
- [81]J.D. Craighead, "Using fractal dimension to assess robot operator skill in a search task," *Journal of Intelligent Robot System*, 2011;64:97-118.
- [82]Ubisense, Inc.: www.ubisense.net
- [83]W.D. Kearns, J.L. Fozard, V.O. Nams, "Movement path tortuosity in free ambulation: relationships to age and brain disease," *Journal of Biomedical and Health Informatics*, 2015;5(1):1-11.
- [84]W.D. Kearns, J.L. Fozard, V.O. Nams, J.D. Craighead, "Wireless telesurveillance system for detecting dementia," *Gerontechnology*, 2011;10: 90-102.
- [85]W.D. Kearns, et al., "Path tortuosity in everyday movements of elderly persons increases fall prediction beyond knowledge of fall history, medication use, and standardized gait and balance assessments," *Journal of the American Medical Directors Association*, 2012;13(7).

- [86]Y. Chang and T. Wang, "Mobile location-based social networking in supported employment for people with cognitive impairments," *Cybernetics and Systems*, 2010;41:245-261.
- [87]E. Batista, F. Borrás, F. Casino, A. Solanas, "A study on the detection of wandering patterns in human trajectories," In 6th International Conference on Information Intelligence Systems and Applications (IISA 2015), 2015.
- [88]A. Solanas, E. Batista, F. Borrás, A. Martínez-Ballesté, C. Patsakis, "Wandering analysis with mobile phones: On the relation between randomness and wandering," In 5th International Conference on Pervasive and Embedded Computing and Communication Systems (PECCS 2015), 2015.
- [89]S. Hossain, K. Hallenborg, Y. Demazeau, "iRoute: Cognitive support for independent living using BDI agent deliberation," in *Trends in Practical Applications of Agents and Multiagent Systems*, ser. *Advances in Intelligent and Soft Computing*, 2011:90:41-50.
- [90]M. Bratman. *Intention, plans, and practical reason*. Harvard Univ Press, Cambridge 1987
- [91]F. Sposaro, J. Danielson, G. Tyson, "iWander: an Android application for dementia patients," 2010, *IEEE EMBC*, 3875-3878.
- [92]J. Hoey, X. Yang, M. Grzes, R. Navarro, J. Favela, "Modeling and learning for LaCasa, the location and context-aware safety assistant," *NIPS 2012 Workshop on Machine Learning Approaches to Mobile Context Awareness*, Lake Tahoe, NV, 2012.
- [93]Q. Lin, D. Zhang, X. Huang, H. Ni, X. Zhou, "Detecting wandering behavior based on GPS traces for elders with dementia," *Proc of the 12th International Conference on Control, Automation, Robotics and Vision*, 2012.

- [94] K.H. Lee, D.L. Algase, E.S. McConnell, "Relationship between observable emotional expression and wandering behavior of people with dementia," *Int J Geriatr Psychiatry*, 2013.
- [95] C.C. Hsiao, "Towards long-term mobility tracking in NTU hospital's elder care center," *PerCom Workshops*, 2011:649-654.
- [96] A. Grünerbl, G. Bahle, P. Lukowicz, F. Hanser, "Using Indoor Location to Assess the State of Dementia Patients: Results and Experience Report from a Long Term, Real World Study," *Proceedings of the 7th International Conference on Intelligent Environments*, 2011.
- [97] D.L. Algase, C. Antonakos, E.R.A. Beattie, C.A. Beel-Bates, L. Yao, "Empirical derivation and validation of a wandering typology," *J AM GeriatrSoc*, 2009;57:2037-2045.
- [98] T. Heart and E. Kalderon, "Older adults: are they ready to adopt health-related ICT?," *Medical Informatics*, 2011:1-23.
- [99] S. Perala, K. Makela, A. Salmenabo, R. Latvala, "Technology for elderly with memory impairment and wandering risk," *e-Health Telecommunication Systems and Networks*, 2013;2:13-22.
- [100] N. Armstrong, C. Nugent, G. Moore, D. Finlay, "Using smartphones to address the needs of persons with Alzheimer's disease," *Ann. Telecommun*, 2010;65:485-495.
- [101] J.C. Hughes, "Electronic tagging of people with dementia who wander: Ethical considerations are possibly more important than practical benefits," *BMJ*, 2002;325(7369):847-848.
- [102] J. Jara, M.A. Zamora, A.F. Skarmeta, "An mHealth platform based on Android OS and 6LoWPAN to support ubiquitous access and data collection," *Journal of eHealth Technology and Application*, Tokai University, 2010;8(1):1-8.

- [103] B.M.C. Silva, J.J.P.C. Rodrigues, I.M.C. Lopes, T.M.F. Machado, L. Zhou, "A Novel Cooperation Strategy for Mobile Health Applications", IEEE Journal on Selected Areas in Communications, Special Issue on Emerging Technologies in Communications - eHealth, 2013;31(9):28-36.
- [104] J. Jara, M.A. Zamora, A.F. Skarmeta, "Interconnection framework for mHealth and remote monitoring based on the Internet of Things", IEEE Journal on Selected Areas in Communications, Special Issue on Emerging Technologies in Communications - eHealth, 2013;31(9):47-65.
- [105] B.M. Silva, J.J.P.C Rodrigues, F. Canelo, I. Lopes, L. Zhou, "A Data Encryption Solution for Mobile Health Applications in Cooperation Environments: DE4MHA", Journal of Medical Internet Research, 2013;15(4).
- [106] APDM Movement Monitoring Solutions, Inc.: www.apdm.com
- [107] D. Martino-Saltzman, B.B. Blasch, R.D. Morris, L.W. McNeal, "Travel behavior of nursing home residents perceived as wanderers and nonwanderers," Gerontologist, 1991;31:666-672.
- [108] Rolland Y, et al. A SPECT study of wandering behavior in Alzheimer's disease: Int J Geriatr Psychiatry 2005;20(9):816-820; DOI: 10.1002/gps.1362.
- [109] Peatfield J, Futrell M, Cox C. Wandering: an integrative review: Journal of Gerontological Nursing 2002;27:45-50; .
- [110] Wang R, et al. Weight loss, nutritional status and physical activity in patients with Alzheimer's disease: Journal of Neurology 2004;251:314-320.
- [111] Ashida N, Makimoto K, Nozaki C, Nakagawa M, Suzuki M. A Monitoring of wandering behavioural pattern of senile dementia with IC tag. 3rd APT Telemedicine, 2005, Kuala Lumpur, Malaysia, pp 80-84

- [112] Algase D, Antonakos C, Beattie E, Hong G, Beel-Bates C. Are wandering and physically nonaggressive agitation equivalent?: Am J GeriatrPsychiat 2008;16(4):293-299; doi:10.1097/JGP.0b013e3181629943.
- [113] Hall M, Frank E, Holmes G, Pfahringer B, Reutemann P, Witten I. The WEKA Data Mining Software: An Update. SIGKDD Explorations 2009;11:1
- [114] Rish I. An empirical study of the naïve Bayes classifier. IJCAI-01 Workshop on Empirical Methods in AI, 2001
- [115] Mitchell T. Machine Learning. New York: McGraw Hill; 1997
- [116] Quinlan J. Induction of decision trees. Machine learning 1986;1(1):81-106
- [117] Darnall N, et al. Application of machine learning and numerical analysis to classify tremor in patients affected with essential tremor or Parkinson's disease: Gerontechnology 2012;10(4):208-219; doi: <http://dx.doi.org/10.4017/gt.2012.10.4.002.00>.
- [118] Breiman L. Random forests: Machine Learning 2001;45(1):5–32
- [119] Friedman J, Hastie T, Tibshirani R. Additive Logistic Regression: a Statistical View of Boosting. Stanford University, 1998
- [120] Breiman L. Bagging predictors: Machine Learning 1996;24(2):123-140
- [121] Boser B, Guyon I, Vapnik V. A training algorithm for optimal margin classifiers. Proceedings of the 5th annual workshop on computational learning theory, 1992, Pittsburgh ACM, pp 144-152
- [122] Fleiss J. Statistical Methods for Rates and Proportions, 2nd ed., John Wiley & Sons, New York, 1981
- [123] E. Keogh, C.A. Ratanamahatana, "Exact indexing of dynamic time warping," Knowledge and Information Systems, 2005;7(3):358-386

- [124] J. Lin, E. Keogh, L. Wei, and S. Lonardi, "Experiencing SAX: a novel symbolic representation of time series," *Data mining and knowledge discovery*, 2007;15:107-144
- [125] SAX tool, <https://cs.gmu.edu/~jessica/sax.htm>
- [126] N.Japkowicz and M. Shah, *Evaluating Learning Algorithms: A Classification Perspective*, Cambridge University Press, 2011
- [127] Kearns W, Nams V, Fozard J. Tortuosity in movement paths is related to cognitive impairment. *Wireless fractal estimation in assisted living facility residents: Methods of Information in Medicine* 2010;49:592-598; doi: 10.3414/ME09-01-0079
- [128] Kearns W, Fozard J, Nams V, Craighead J. Wireless telesurveillance system for detecting dementia: *Gerontechnology* 2011;10:90-102; doi: <http://dx.doi.org/10.4017/gt.2011.10.2.004.00>
- [129] R. Vera-Rodriguez, J. Mason, J. Fierrez, and J. Ortega-Garcia, "Comparative analysis and fusion of spatiotemporal information for footstep recognition," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 35, no. 4, pp. 823–834, April 2013.
- [130] Mihai Andries, Olivier Simonin, Francois Charpillet. Localisation of humans, objects and robots interacting on load-sensing floors. *IEEE Sensors Journal*, Institute of Electrical and Electronics Engineers, 2015, PP (99), pp.12.
- [131] M. Valtonen, J. Maentausta, and J. Vanhala, "TileTrack: Capacitive Human Tracking Using Floor Tiles," in *IEEE International Conference on Pervasive Computing and Communications*, 2009, pp. 1-10.
- [132] H. Rimminen, J. Lindström, and R. Sepponen, "Positioning Accuracy and Multi-target Separation with a Human Tracking System Using Near Field Imaging," *Smart Sensing and Intelligent Systems*, vol. 2, No. 1, pp. 156–175, 2009

- [133] I. Al-Naimi, C. B. Wong, "Indoor human detection and tracking using advanced smart floor," in Information and Communication Systems (ICICS), 2017 8th International Conference on, April 2017, pp. 1–6.
- [134] T. Teixeira, G. Dublon, and A. Savvides, "A survey of human-sensing: Methods for detecting presence, count, location, track, and identity," ACM Comput. Surveys, vol. 5, issue 1, pp. 59–69, 2010.
- [135] W.-H. Liao, C.-L. Wu, and L.-C. Fu, "Inhabitants Tracking System in a Cluttered Home Environment Via Floor Load Sensors," IEEE Trans. on automation science and engineering, vol. 5, no. 1, pp. 10–20, January 2008.
- [136] A. Braun, H. Heggen, and R. Wichert, "Capfloor - a flexible capacitive indoor localization system," in Evaluating AAL Systems Through Competitive Benchmarking. Indoor Localization and Tracking, ser. Communications in Computer and Information Science, S. Chessa and S. Knauth, Eds. Springer Berlin Heidelberg, 2012, vol. 309, pp. 26–35.
- [137] C. Lauterbach, A. Steinhage, and A. Techmer, "Large-area wireless sensor system based on smart textiles," in Systems, Signals and Devices (SSD), 2012 9th International Multi-Conference on, March 2012, pp.1–2.
- [138] Tarkett, "FloorInMotion." [Online]. Available: <http://www.floorinmotion.com/>
- [139] J. A. Cantoral-Ceballos, N. Nurgiyatna, P. Wright, J. Vaughan, C. Brown-Wilson, P. J. Scully, and K. B. Ozanyan, "Intelligent carpet system, based on photonic guided-path tomography, for gait and balance monitoring in home environments," IEEE Sensors J., vol. 15, no. 1, pp. 279–289, Jan. 2015.

- [140] M. Daher, A. Diab, M. El Badaoui, El Najjar, M. Ali Khalil, F. Charpillat, "Elder Tracking and Fall Detection System Using Smart Tiles", IEEE Sensors Journal, vol. 17, pp. 469-479, 2017.
- [141] C.Y. Huang, K.W. Chang, C.Y. Tai, W.T. Chen, Y.L. Hsu, "Development of a smart living platform based on a motion sensing carpet," Consumer Electronics - Taiwan (ICCE-TW), 2017 IEEE International Conference on, 2017

Appendix A: Movement records of subjects A, B, C, D, E

Appendix A presents the movement records of subjects A, B, C, D, E used in experiments in Chapter 4, Section 2. In Figs. A.1-A.3, the location and time data are represented in the vertical and horizontal axis respectively. In Figs. A-1 and A-2, the black lines indicate the movements within an episode of walking. The green lines indicate the continuity of the movements of the subjects.

Figure A.1: Movement records of subjects A and B [70].

Subject
C

Subject
D

Figure A.2: Movement records of subjects C and D [69].

Subject E

Figure A.3: Movement records of subject E [69].

Appendix B: Classification results in uncontrolled study

Appendix B reports the classification results of all the subjects used in the uncontrolled study in Chapter 5, Section 4. In Figs. B.1-B.23, the orientation signals and the signals represented by reserve-SAX are drawn together. The title of each figure details the subject number, the series number of the pattern to be classified, and the class (direct, pacing, lapping, and random) classified by the proposed algorithm.

Figure B.1: Classification results of subject 1

Figure B.2: Classification results of subject 2

Figure B.3: Classification results of subject 3

Figure B.4: Classification results of subject 4

Figure B.5: Classification results of subject 5

Figure B.6: Classification results of subject 6

Figure B.7: Classification results of subject 7

Figure B.8: Classification results of subject 8

Figure B.9: Classification results of subject 9

Figure B.10: Classification results of subject 10

Figure B.11: Classification results of subject 11

Figure B.12: Classification results of subject 12

Figure B.13: Classification results of subject 13

Figure B.14: Classification results of subject 14

Figure B.15: Classification results of subject 15

Figure B.16: Classification results of subject 16

Figure B.17: Classification results of subject 17

Figure B.18: Classification results of subject 18

Figure B.19: Classification results of subject 19

Figure B.20: Classification results of subject 20

Figure B.21: Classification results of subject 21

Figure B.22: Classification results of subject 22

Figure B.23: Classification results of subject 23