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Chai, Chen; Shi, Xiupeng; Wong, Yiik Diew; Er, Meng Joo; Gwee, Evan Tat Meng

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Fuzzy logic-based observation and evaluation of pedestrians' behavioral patterns by age and gender

Abstract:

Pedestrian behavior is affected by a multitude of factors such as age, gender, operating conditions, etc. However, traditional statistical analysis based on observed movements or questionnaire survey is unable to model decision-making process of each pedestrian. This study develops an innovative approach based on fuzzy logic to extract the underlying cognitions and behavioral patterns of pedestrians. Membership functions link deterministic input/output with linguistic terms and these membership functions serve to provide understanding of the subjective cognitive judgments of a pedestrian. To evaluate age and gender effect, field observations are conducted at two types of pedestrian movements namely, jaywalking and crossing a signalized crosswalk. Fuzzy sets and rules are created to model the relationship between human cognitions and decisions of an individual pedestrian. Through calibrating the membership functions of different age and gender groups, behavioral patterns of pedestrians are evaluated and compared. Different from most previous studies, both older and younger pedestrians are found to be less risk-taking than adult pedestrians. Moreover, significant gender difference is found only for cognitions of most hazardous conditions. Consistent with previous studies, it is seen that men have better cognitive skills than women at detecting hazardous situations.

Keywords:

Pedestrian behavior; Age and gender differences; Fuzzy Logic; Jaywalk; Signalized crosswalk

1 Introduction

Age and gender are known to affect pedestrians' behavioral patterns. Their effects are reflected in the accident records. In Singapore in 2014, there were 435 accidents between pedestrians and vehicles that the pedestrians were likely at fault (Singapore Police Force, 2015), and were ascribed to three major contributory factors: crossing heedless of road traffic (40%), failing to use available pedestrian crossing (8%), and crossing within pedestrian crossing but during red man pedestrian signal (11%). It is found that elderly pedestrians (above 50 years old) are disproportionately represented in accidents involving these three factors (at 33%, 26%, and 19%) given the elderly population base of 11.1% (National Population and Talent Division, 2012). This may be attributed to the elderly pedestrians being less agile, tendency to walk slower and have longer reaction time (Tarawneh, 2001; Holland and Hill, 2010). Gender differences are also evident in the accident records. Male pedestrians are involved in 60% and 64% of the accidents ascribed to crossing heedless of traffic and crossing during red lights

compared to 40% and 36% for female pedestrians. This is consistent with previous observations that male pedestrians committed significantly more violations than females (Rosenbloom et al., 2004).

Analysis based on crash records is confounded by issues such as the random nature of crashes as well as different degrees of mobility across the age and gender groups (Liu and Tung, 2014). To better understand behavioral patterns of pedestrians as affected by age and gender, this study undertakes observations of the pedestrian movements to develop a novel evaluation approach based on fuzzy logic technique. The outline of this paper is as follows. Section 2 is on literature review that highlights the significance of the proposed fuzzy logic approach by critically reviewing existing studies. Section 3 introduces the field observation study and layout of the proposed fuzzy logic approach. In Section 4, pedestrians' age and gender factors are evaluated through the calibration of membership functions. The paper ends with conclusions and discussions of the advantages and limitations of the applied fuzzy logic approach.

2 Background

2.1 Effect of age and gender on pedestrians' cognition of risk

Age and gender traits are important factors of pedestrians' risk as related to road safety, hence it is a very important issue to understand how age and gender contributes to these risks (UK Department of Transport, 2004). Some researchers ascribed the higher risk of elderly or women pedestrians to the greater amount of walking and thus being more exposed to risky situations. However, such argument is questionable given that though elderly pedestrians or women drive less, the distance walked according to age and gender groups is not compared (Carthy et al., 1995).

In recent years, studies have differentiated the cognitive attributes, such as perception, attitude and intention, by age and gender groups. Younger road users are more prone to take risk and are less skillful in perceiving hazards as cognitive and sensory skills improve with age (Parker et al., 1996; Dunbar et al., 2004). Experiences of being a driver also affect risk-taking behavior of the pedestrians (Groeger, 2002). As men usually drive more than women, they possess different perception skills (Holland and Hill, 2007). It is also found that attitude and intention affects risk-taking behavior by age and gender (Elliott et al., 2003). Since cognitions play a very important role in age and gender differences, some researchers have applied the theory of planned behavior (TPB) model, which involves perception and intention of human, to examine pedestrians' behavioral patterns. Evans and Norman (1998) applied TPB to analyze adults' road crossing behavior for three risky situations. It is found that perceptions and attitudes accounted for 39%–52% of the variance in intention to cross the road. Elderly pedestrians are also found to be more likely to make risky road crossing than other age groups, but gender differences are not found in this study. A study by Diaz (2002)

compared adults under and above 26 years old. It is found that younger people are more risk-prone towards crossing the road. As in Evans and Norman's study, gender difference is not found in Diaz's study. Therefore, the key aim of the present study is to examine whether there is cognition difference of pedestrians by age and gender. Specifically, the following aims are investigated:

1. To find whether older and female pedestrians are less risk-taking than other age and gender groups.
2. To provide a mathematical approach to model, and estimate, the cognitions of pedestrians by age and gender groups.
3. To examine how age and gender traits vary under different situations, for example, jaywalking or walking-on-red at signalized pedestrian crosswalks.

2.2 Existing approaches on behavioral study

Existing approaches on understanding pedestrian behavior can be classified in two groups, namely field observation, and questionnaire survey. Observation study based on video recordings provides direct access to detailed pedestrian movements. Instead of relying on some kind of self-report, such as questionnaire survey, actual behavior under various situations are observed and recorded. Behavioral patterns have been analyzed by numerous researchers based on observational data (Brosseau et al., 2013; Lipovac et al., 2013). In Singapore's local context, Koh et al. (2014) used video recording to study pedestrian behavior and violations at signalized pedestrian crosswalks.

Questionnaire survey, on the other hand, focuses more on pedestrians' attitude (Sisiopiku and Akin, 2003). Muraleetharan et al. (2004) estimated level of service at four sidewalks and crosswalks based on interviewing pedestrians. Origins of rule-breaking of pedestrians at train stations are examined through a questionnaire survey conducted by Freeman and Rakotonirainy (2015). Even though the questionnaire survey is a direct approach to examine pedestrians' attitudes and intentions, the results may be biased as the participant may not fully understand the survey form adequately or be able to 100% correctly report his or her attitude and intention about past scenarios. Moreover, it is almost impossible to examine pedestrians' attitude at different locations or traffic conditions through a questionnaire survey. An approach that can examine pedestrians' cognitions from observed movements is therefore of great significance.

2.3 Fuzzy logic-based decision-making models

Fuzzy logic (FL) theory can be aptly applied to model human factors (Lim et al., 2015). Compared to traditional logic with exact and fixed solution, fuzzy logic contains uncertainty and approximation which are well suited to representing multiple co-operations, collaboration and even conflicts (Chiou and Huang, 2013). Incorporation of fuzzy control in evaluating behavioral patterns of pedestrians enables linkage of cognitions with the observed behavior. Linguistic terms are used in fuzzy logic to

describe environment and responses (Adeli and Jiang, 2003). These linguistic terms can be used to describe pedestrians' cognitions, such as perception, intention and attitude. In this way, decision-making procedure of individual pedestrians can be analyzed in a very clear and straight-forward way.

In earlier studies, fuzzy rules have been applied to describe driving behavior of vehicles (Wu et al., 2000). Drivers' behavior in the dilemma zone at signalized intersections has been modeled using fuzzy sets (Hurwitz et al., 2012). As most current approaches focuses on the driving behavior, this study aims to extend current applications of fuzzy logic into the study of pedestrian behavior. Through modelling the decision-making process based on fuzzy sets and rules, cognitions of individual pedestrians are estimated.

3 Methodology

3.1 Field observation

Field observations are conducted at one jaywalk location (Site A) and one pedestrian crosswalk (Site B) in Singapore as shown in Figures 1a and 1b. Site A is a 5-lane road (16.5m wide) between a bus stop at one side and a large residential area including 3 residential buildings, a large supermarket and a foodcourt at the other side. As the bus stop is about 150m away from the nearby signalized crosswalk, some pedestrians choose to jaywalk. Site B is a signalized pedestrian crosswalk of 3m in width and 15.7m in length. Green time ranges from 18s to 25s while signal cycle ranges from 84s to 103s. The field observations were made on 2:00-3:00 pm during weekdays.

A computer-aided manual tracking technology is used to record pedestrian's position, velocity and forwarding direction, as shown in Figure 1c (Chai and Wong, 2013). Position of pedestrian is recorded by manually labeling them at each video frame, as shown in Figure 1c. Projective transformation is applied to compute global position and velocity after tracking. Figures 1d and 1e show the trajectory and velocity profiles of a tracked pedestrian. Five age and gender groups are created and classified based on subjective judgment of the data analyst. The classification might be biased by the data analyst, especially to distinguish teenager and young adults. Therefore, as video recording is conducted during 2-3pm on weekdays, young pedestrians wearing school uniforms are classified as teenagers while those who look around 20 years or older but not wearing uniforms are classified as adults. A total number of 1335 pedestrians were observed, as summarized in Table 1.

Figure 1 Field observation and pedestrian tracking

Table 1 Observed pedestrians in different age and gender group

	Age	Gender	Number
1	Children/ Teenager	Male	315
2	Children/ Teenager	Female	291
3	Adult	Male	264
4	Adult	Female	240
5	Elderly pedestrian	Male	95
6	Elderly pedestrian	Female	130

3.2 Proposed fuzzy logic approach

3.2.1 Cognition system of individual pedestrian

The cognition system of on individual pedestrian is examined to find out factors affecting decision-making process of individuals. According to Figure 2, cognitions can occur on three levels, environment, physiology and psychology. The status of the subject pedestrian describes his/her current position and velocity, whether the pedestrian is walking in a group and its current personal space. Perception of pedestrian covers the environment attributes that pedestrians were observed while walking. Desired position, velocity and personal space are classified as pedestrian's intention. Attitude of pedestrians includes risk-taking behavior and tolerance of small spaces. Even though the cognitions are classified at different levels, as represented in Figure 2, they may occur on more than one level and affect each other. Decisions, on the other hand, stem from all these cognitions involving psychological reasoning, physiological factors, and external environment.

Figure 2 Cognition system of individual pedestrian

3.2.2 Logical basis of the proposed approach

In this study, the cognition system is modeled by fuzzy inputs while pedestrian decisions are modeled by fuzzy outputs, as shown in Figure 3. The fuzzy system contains three steps: Fuzzification is to convert observed input parameters to linguistic terms based on the membership functions. Rule evaluation is to compute decisions based on pre-defined fuzzy rules. Since the decisions after rule evaluation is a linguistic term, the last step is to defuzzificate decisions based on their membership functions and to compute decision of each individual pedestrian. Centroid difuzzification method is applied to return the centroid of aggregated conclusions from each fuzzy rule (Chiou and Huang, 2003).

Figure 3 Operation diagram of fuzzy system

The operation diagram of fuzzy system is the logic basis of the proposed approach. Firstly, exact values of input and output parameters are observed from field study as introduced in section 3.1. Since fuzzy rules and sets can be defined by the analyst, the

only unknown part of the operation diagram is the membership functions of input and output parameters. Definition of membership functions are shown in Figure 4. The x axis is input factors while the y axis is membership degree (μ_x) for each linguistic term, in a [0,1] interval. For a deterministic parameter (x_1), the values of membership functions ($\mu_1, \mu_2, \dots$) represents the probabilities of x_1 belonging to each linguistic term. As membership functions link deterministic input/output and linguistic terms, obtaining these membership functions serves to understand the subjective judgment on status and perception of each pedestrian.

Figure 4 Membership functions

3.2.3 Fuzzy sets and rules

As summarized in Table 2, two sets of fuzzy rules, named as F_1 to F_2 , are defined to model pedestrian stop/go decisions (SG) and velocity change (φ) (Wijermans, 2011; Zeng et al., 2014). SG is a 0, 1 number (0=stop, 1=go) while φ is the acceleration or deceleration rate. Different inputs are applied for pedestrians at jaywalk and signalized crosswalk. For example, stop/go decision of a jaywalking pedestrian is affected by whether the subject pedestrian is walking within a pedestrian group, his/her current position, velocity of the first upcoming vehicle and relative gap between subject and the first upcoming vehicle. For pedestrians at signalized crosswalks, the stop/go decision is also affected by signal timing. Furthermore, as part of a bi-direction flow, pedestrians at signalized crosswalks are also affected by relative gap and velocity of oncoming pedestrians (Chai et al., 2015). Linguistic terms are used to describe each input and output. To simplify computation, inputs are classified as common inputs, and two separate input groups that contain upcoming pedestrians and vehicles. Decisions affected by common inputs and each input group are computed simultaneously as (SG^1, SG^2) and (φ^1, φ^2) . Therefore, for jaywalk pedestrians, only one decision is computed while for pedestrians at signalized crosswalks two decisions are combined according the following Equations 1 and 2.

$$SG = \min(SG^1, SG^2) \quad (1)$$

$$\varphi = \min(\varphi^1, \varphi^2) \quad (2)$$

Fuzzy rules are created based on rational sense to describe the desired response of each pedestrian. For example:

Fuzzy Set F₁ Rule No.1:

If **Signal timing is Just become green**,

AND **Current position is Before stop-line/ Before jaywalking**,

AND **Relative gap between first upcoming vehicle is Far**

Then **Stop/go decision (SG) is Go**;

Table 2 Input factors of fuzzy sets

	Inputs	F ₁ : Stop/go decision		F ₂ : Velocity change	
		Jaywalk	Crosswalk	Jaywalk	Crosswalk
Common inputs	Signal timing {Just become green; About to become red; Red can cross; Red cannot cross};		○		○
	Current position {Before stop-line/ before jaywalking; Near end; Middle; Far end}	○	○	○	○
Group 1 (upcoming pedestrian)	Relative gap between upcoming pedestrian {Far; Medium; Close};		○		○
	Relative velocity between upcoming pedestrian {Opening fast; Opening; About zero; Closing; Closing fast }		○		○
Group 2 (upcoming vehicle)	Relative gap between first upcoming vehicle {Far; Medium; Close}	○	○		
	Velocity of upcoming vehicle {Fast; Medium; Slow }	○	○		

3.3 Calibrating membership functions

Membership functions of input factors for each fuzzy set are derived according to observed pedestrian movements, membership functions, and defined fuzzy rules. In most previous studies, it is assumed that membership functions are triangular and trapezoidal, as linear functions lead to better computational efficiency. In this study, to achieve better accuracy, three common types of membership functions, Linear (Triangular or Trapezoidal), Gaussian, and Sigmoidal, as shown in Equations 3 to 7 and Figure 5 are tested. Gaussian functions are built on Gaussian distribution curve to achieve smoothness. The combination functions are used to specify unsymmetrical

functions as shown in Figure 5d. Different from Gaussian function, sigmoidal function can be applied to specify one-sided smoothed functions, as shown in Figure 5e. Two-sided asymmetric cases can be achieved by product of two sigmoidal functions (see Equation 8). The difference between product of two sigmoidal functions and Gaussian combination function is that Gaussian functions are non-zero at all points.

Figure 5 Membership function types

Linear membership functions:

$$\text{Triangular: } f(x; a, b, c) = \max\{\min[(x-a)/(b-a), (c-x)/(c-b), 0]\} \quad (3)$$

$$\text{Trapezoidal: } f(x; a, b, c, d) = \max\{\min[(x-a)/(b-a), 1, (d-x)/(d-c)]\} \quad (4)$$

$$\text{Gaussian membership functions: } f(x; \sigma, c) = e^{-(x-c)^2/2\sigma^2} \quad (5)$$

Gaussian combination membership functions (asymmetrical):

$$f(x; \sigma_1, \sigma_2, c_1, c_2) = \begin{cases} e^{-(x-c_1)^2/2\sigma_1^2} & \text{left - most curve} \\ 1 & \text{if } c_1 < c_2 \\ e^{-(x-c_2)^2/2\sigma_2^2} & \text{right - most curve} \end{cases} \quad (6)$$

$$\text{Sigmoidal membership functions: } f(x; a, c) = 1/[1 + e^{-a(x-c)}] \quad (7)$$

$$\text{Product of two sigmoidal functions: } f(x; a_1, a_2, c_1, c_2) = 1/[1 + e^{-a_1(x-c_1)}] \times [1 + e^{-a_2(x-c_2)}] \quad (8)$$

where x is the input value, a , b , c , d and σ are the scalar parameters depending on the membership degree.

The methodology to calibrate membership functions of each input consists of three steps, as shown in Figure 6. First, pedestrian decisions are classified into several groups based on the number of linguistic terms of the input factor. As average perception-response time (PRT) at pedestrian crossings is set as 1s, pedestrians' response at each time is determined by surrounding conditions 1s earlier. Frequencies of input values (1s ago) are computed in each decision group. After that, frequencies of each group are divided by the summation of frequencies from two groups. Based on the frequencies distribution, membership functions are calibrated using curve fitting approaches. The detailed calibration procedures are described in the two following examples, as shown in Figures 6 and 7.

Figure 6 Calibrating membership functions (relative gap along moving direction)

First, membership functions of relative velocity of upcoming pedestrian (Slow, Medium, Fast) are estimated based on velocity change (Walk faster, Keep walking, Walk slower) at signalized crosswalk. As average and maximum acceleration and deceleration rates are known from field observations, membership function of velocity change can be

plotted as shown in Figure 6a. Assume the other factor (relative velocity) follows a normal distribution. When relative gap is Close, velocity change will be slower. Therefore, according to membership functions and fuzzy rules, velocity change can be classified in three ranges, as shown in Figure 6b. Figures 6c to 6e shows the relationship between relative gap and frequencies of making each decision. Membership function of this factor is then calibrated as Figure 6f and Equations 9-11. The membership function of 'Medium' is then derived as the submission of all membership functions must be 1 at each input (relative gap) value.

$$\text{Close:} \quad f(x) = 1/[1 + e^{-0.3459(x-25.66)}] \quad (9)$$

$$\text{Medium:} \quad f(x) = 1 - 1/[1 + e^{0.1482(x-75.3)}] - 1/[1 + e^{-0.3459(x-25.66)}] \quad (10)$$

$$\text{Far:} \quad f(x) = 1/[1 + e^{-0.1482(x-75.3)}] \quad (11)$$

where x is the relative gap.

Another example is to estimate the membership functions of gap between upcoming vehicle (Close, Medium, Far) based on stop/go decisions calibrated at jaywalk. Assume the other factors follow a normal distribution, the following conclusions can be obtained from fuzzy rules: when gap between upcoming vehicle is Far, pedestrian's stop/go decision will be Go; when gap is Close, stop/go decision will be Stop. Frequencies of input values in the stop group are computed as Figures 7a. 10th, 50th, and 90th of distribution of frequencies are therefore used to generate the three groups, as the vertical blocks in Figure 7a. Membership function of this factor is then calibrated as Figure 7b.

Figure 7 Calibrating membership functions for gap between upcoming vehicle
(Solid line: Close; Dash line: Medium; Dot line: Far)

4 Results and Discussions

In-terms of risk-taking behavior, perception, attitude and intention are found to affect each other (Azjen, 1991). Therefore, in this study, combined cognitions are analyzed from calibrated input factors. For example, if a subject pedestrian judges his/her

relative distance to the first upcoming vehicle as “Far”, no matter whether it is affected by perception, attitude and intention, the judgment itself is analyzed as a cognition. This section analyzes calibrated memberships and compares cognitions of different age and gender groups. Age and gender differences as affecting pedestrians’ cognitions in response of upcoming vehicles and signal timing are then discussed.

4.1 Cognitions to upcoming vehicles

As introduced in Section 3.2, the fuzzy inputs (relative gap between the first upcoming vehicle, and velocity of the first upcoming vehicle) are built to determine stop/go decisions and velocity changes of each individual. The membership functions of these two inputs are calibrated for each age and gender group at both jaywalk and signalized crosswalk. As shown in Figures 8, there are nine different combined memberships (No. 1 to 9) of relative velocity and gap. The value of the z-axis represents probability of a subject pedestrian to make a judgment based on the value of x and y axes. No. 1 is the most hazardous pedestrian cognition as relative gap is close and velocity of vehicle is fast. No. 2, 4 and 5 are less hazardous than No.1 but pedestrians will still choose to stop.

Figure 8 Combined membership functions of 9 possible cognitions (all age and gender groups)

4.2 Differences of cognitions affected by age and gender factors

Combined membership functions in different age and gender groups are then computed. Two-sample Kolmogorov-Smirnov (KS) tests are conducted to compare membership

functions at the 5% significant level. The null hypothesis (H_0) is defined as being equal. Test results and p values are summarized in Table 5. If the test result is 1, the two memberships are found to be significantly different at 5% level. At the same time, smaller p value (in blankets in Table 5) represents larger difference. Different test results from Cognitions No. 1 and No. 4 between the same pair of age and gender groups are marked as bold font.

The results are presented in three parts: age differences, gender differences, and additional findings as shown in Table 5.

1) Cognitions affected by age

According to Table 5, in both Cognition No. 1 and 4, significant age differences are observed between elderly pedestrian and adult pedestrian. In general, elderly pedestrians are less risk-taking than the other two age groups. Furthermore, in Cognition No. 4 (Distance: Medium, Velocity: Fast), significant effect between young and adult groups are observed. However, different from previous studies, young pedestrians are found to be less risk-taking than adults. One of the main reasons is that in this study young pedestrians are within the age group of under 20 years and most observed pedestrians are in or below high school while existing studies define young pedestrian as under 26 years old. Another possible reason is that previous studies based on questionnaire survey could be biased as adult pedestrians may try not to self-report the “true” (risk-taking) attitude.

2) Gender differences

Gender differences are also observed in Table 5. In Cognition No. 1, female pedestrians are found to be significantly less risk-taking. In the less hazard cognition (No. 4), no significant difference between the two genders is observed. Furthermore, to test whether effect of gender exists in Cognition No. 4, the same hypothesis is tested at 10% significant level and H_0 is still rejected. The result is consistent with previous finding from other researchers that women are less sensitive to hazard situations.

3) Correlations of age and gender

To further examine whether correlations exist between age and gender, KS tests are conducted for all the six age and gender group, as classified in Table 1. According to the right half of Table 5, several findings can be made. First, within male pedestrians, effect of age only occurs between young and adult groups in Cognition No. 4. However, effect between young and adult women occurs in both cognitions (1 and 4). It is also found that gender effect is found in most age and cognition groups, but not between older male and female pedestrians. One of possible reasons is lesser perambulation for both female and male elderly pedestrians which make them more cautious than other age groups. Last but not least, compared to the most hazard cognition (No. 1), lesser effect is found between adult male and female pedestrians for the lesser hazardous cognition.

Table 5 Results of KS tests in different age and gender groups

Cognition No. 1 (Distance: Close, Velocity: Fast)											
Pedestrian group	Differences by age factor				Pedestrian group	Young male (1)	Young female (2)	Adult male (3)	Adult female (4)	Older male (5)	Older female (6)
	Young (1+2)	Adult (3+4)	Older (5+6)								
Young (1+2)	NA	0 (0.3708)	+1* (0.2513)		Young male (1)	NA	0 (0.5295)	0 (0.1949)	1 (1.5×10 ⁻⁹)	1 (4.2×10 ⁻¹⁵)	1 (6.0×10 ⁻²⁰³)
Adult (3+4)		NA	-1 (2.8×10 ⁻³)		Young female (2)		NA	0 (0.2811)	1 (5.4×10 ⁻⁵)	1 (3.8×10 ⁻⁴⁵)	1 (6.0×10 ⁻¹⁷²)
Older (5+6)			NA		Adult male (3)			NA	1 (9.4×10 ⁻²³)	1 (4.2×10 ⁻³⁵)	1 (9.3×10 ⁻⁹²)
	Differences by gender factor				Adult female (4)				NA	1 (6.8×10 ⁻⁶)	1 (5.7×10 ⁻³¹)
Male (1+3+5)	Female (2+4+6)	+1 (2.1×10 ⁻¹³)			Older male(5)					NA	1 (0.0319)
					Older female (6)						NA
Cognition No. 4 (Distance: Medium, Velocity: Fast)											
Pedestrian group	Differences by age factor				Pedestrian group	Young male (1)	Young female (2)	Adult male (3)	Adult female (4)	Older male (5)	Older female (6)
	Young (1+2)	Adult (3+4)	Older (5+6)								
Young (1+2)	NA	+1 (0.4391)	1 (6.1×10 ⁻¹⁴)		Young male (1)	NA	0 (0.1347)	1 (4.5×10 ⁻⁰⁸)	0 (0.5661)	1 (2.9×10 ⁻⁹³)	1 (1.1×10 ⁻⁷¹)
Adult (3+4)		NA	-1 (2.5×10 ⁻¹⁸)		Young female (2)		NA	1 (2.0×10 ⁻⁷⁸)	1 (2.0×10 ⁻³⁸)	1 (2.5×10 ⁻¹⁸)	1 (2.8×10 ⁻⁷)
Older (5+6)			NA		Adult male (3)			NA	0 (0.0313)	1 (1.8×10 ⁻⁴³)	1 (1.8×10 ⁻⁵³)
	Differences by gender factor				Adult female (4)				NA	1 (1.7×10 ⁻⁷⁸)	1 (3.3×10 ⁻⁴³)
Male (1+3+5)	Female (2+4+6)	0 (0.0219)			Older male (5)					NA	0 (0.0123)
					Older female (6)						NA

*: -1 represents smaller membership function (less risk-taking), +1 represents larger membership function (more risk-taking) based on 1-side test at 2.5% significance level

4.2 Additional findings

Apart from age and gender effect, other factors affecting cognitions and behavioral patterns are also examined by calibrated fuzzy membership functions, as shown in Figure 9. The following sections analyzes the effect of group size and the differences between jaywalk and signalized crosswalk.

Figure 9 Comparison between group size and locations

1) Behavioral differences at jaywalk and signalized crosswalk

As signalized crosswalk is a signal control to guide pedestrians' behavior, membership functions calibrated from jaywalk and signalized crosswalk is compared to examine the cognition and behavioral differences at these two locations. Figures 9a and 9b show membership functions of close distance and far distance at jaywalk, and green man and red man at signalized crosswalk. It is found that the behavior at close distance is similar

at jaywalk and red man signal. Pedestrians during green man signal are relatively more risk-taking. According to Figure 9b, during green man signal, pedestrians are also more decisive to make a judgment at far distance. It is also found that pedestrians at jaywalk are slightly more risk-taking than at red man signal. This may due to higher velocity of conflicting vehicles during the red man signal as from drivers' perceptive, they are more likely to accelerate during their green signal (Chai, 2015).

2) Group size

In previous studies, group size is found to be a significant factor affecting risk-taking behavior of pedestrians. Some studies found that larger groups of pedestrians are associated with lower likelihood to violate the red light (Rosenbloom, 2009). In this study, the membership functions of Close relative gap between upcoming vehicles is calibrated for different group sizes at both jaywalk and signalized crosswalk, as shown in Figures 9b to 9d.

According to Figures 9c to 9f, group size affects membership functions principally for far distance. It is found that pedestrians in a group are not significantly more risk-taking. However, compared to individual pedestrians, groups are easier to predict low risk-taking according to traffic conditions. However, the effect is smaller at jaywalk than signalized crosswalk, especially between small and large groups.

5 Conclusions

This study applies fuzzy logic to examine differences in cognition for age and gender traits at jaywalk and signalized crosswalk. Pedestrian movements are observed by field observations and pedestrian tracking. Fuzzy sets and rules are defined to model decision-making process affected by signal timing, pedestrian group, upcoming vehicles and oncoming pedestrians. Through calibrating membership functions, age and gender differences on pedestrian behavior are examined in various situations.

According to calibrated membership functions, both age and gender are found to have significant influence on cognitions and behavioral patterns. Different from most previous studies, both older and younger pedestrians are found to be less risk-taking than adult pedestrians. Moreover, males are significantly more risk-taking in only the highest hazard cognition. This is consistent with previous studies suggesting that men have better detection skills of hazard situations than women.

Apart from age and gender effect, other factors that affect cognitions and behavioral patterns are found from calibrated fuzzy membership functions. It is seen that pedestrians at jaywalk are slightly more risk-taking than walking-on-red-signal. The effect of group size is also examined in this study. Pedestrians in a group are not more risk-taking, and are easier to predict low risk-taking according to traffic conditions

From this study, a new approach based on fuzzy logic is developed. Through incorporating fuzzy sets and linguistic terms, actual measurements from field observations are converted to (cognition) linguistic terms. Moreover, calibrated membership functions allow better understanding of the subjective judgment on cognitions for each pedestrian. Compared to traditional approaches, the new approach based on fuzzy logic is more accurate, less time consuming than questionnaire survey and allow engineers to examine both cognitions and movements of the pedestrians. Improvements can be made to refine and extend the applications of fuzzy logic method in future work. For example, driving/walking experiments (based on real driving/walking or simulator) and questionnaire surveys can be conducted to further understand the behavior, perception and attitude of road users.

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