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Modeling and simulation of pedestrian dynamical behavior based on a fuzzy logic approach

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ABSTRACT

This study proposes a fuzzy logic approach to model and simulate pedestrian dynamical behaviors, which takes full advantage of human experience and knowledge and perceptual information obtained from interactions with surrounding environments. First, the radial-based method is adopted to represent the physical space. A pedestrian's visual field, defined as a fan-shaped area with a certain visual distance and visual angle, is divided into five sectors. Then, the motion states of a pedestrian are determined by the integration of recommendations of local obstacle-avoiding behavior, regional path-searching behavior and global goal-seeking behavior with mutable weighting factors at three different scopes. These elementary behaviors and weighting's assignment principle are modeled as fuzzy inference systems with the input information of a pedestrian's perception toward surrounding environments. A pedestrian is guided to avoid the front obstacles and select the lowest negative energy path by local obstacle-avoiding behavior and regional path-searching behavior, respectively. The global goal-seeking behavior makes a pedestrian has a tendency of moving in direction of his/her goal regardless of external environments. The magnitudes of weighting factors are adjusted automatically to coordinate three elementary behaviors and resolve potential conflicts. At last, the effectiveness of the proposed model is validated by simulations of crowd evacuation, unidirectional and bidirectional pedestrian flows. The simulation results are analyzed from both qualitative and quantitative aspects, which indicate that the fuzzy logic based pedestrian model can get true reappearance of self-organization phenomena such as 'arching and clogging', 'faster-is-slower effect' and 'lane formation', and the fundamental diagrams are in matching with a large variety of empirical and experimental data. A further study finds that walking habits have negligible influence on the fundamental diagrams of bidirectional pedestrian flow at least for densities of $\rho < 3\text{p/m}^2$.

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1. Introduction

The modeling of pedestrian dynamics as an interdisciplinary research direction has attracted a wider interest of researchers and managers. The traffic capacity at the passage, characteristic features of normal and escape panics, and self-organization phenomena of crowds have been taken into account by architects and designers for optimization of limited traffic resources and formulation of urgent evacuation plans.

In order to understand complicated motion features of pedestrians, the important work is to build a suitable model for characterization of pedestrians' behaviors. Many prior studies on pedestrian dynamics have presented various pedestrian (crowd) models. The state of art of the models is mainly based on the following three type of methods: macroscopic, mesoscopic and microscopic model. The first, which treats the crowds as a fluid or continuum, uses gas kinetics and hydrodynamics to describe large crowds [24,25,60]. The second, which doesn't differentiate between individual pedestrians, focuses on describing part of global properties of pedestrians[21,22]. The third, which can analyze and research individual behaviors with the interplay of pedestrians, always treats a pedestrian as a discrete individual driven by force, potential or utility [1,5,20]. In the last years much more attention has been focused on microscopic modeling, where the socio-psychological and complex interactions of individuals and environments are considered in the model. Examples of microscopic models are the social force model [18,20], cellular automata model [5,46], lattice gas model [38,48], discrete choice model [1], agent-based model [41], and game theoretic model [4,29]. As a kind of highly complex living organisms, the behaviors of a pedestrian are jointly determined by personal internal consciousness and external environments. It is difficult to propose a mathematic model describing and predicting a pedestrian's behaviors accurately, especially given the complex interactions with surrounding environments.

The environmental effect is a critical factor in modeling of pedestrian dynamics, and it varies significantly over time and space. Researchers in various disciplines have made tremendous efforts to specify the stimuli of surrounding environments, including pedestrians, groups, obstacles, exits and so on, on pedestrian dynamic behaviors from different perspectives. The level of environmental stimuli is specified as physical force [18,20], floor field [5,46], drift (bias) [38,48], utility [1], and payoff [4,29] for quantitative evaluation of environmental factors in the previous studies. For example, Helbing et al. [18,20] modeled the effects of surrounding pedestrians and walls as interaction forces which shows a negative exponential decline with distances. In mathematical terms, the change of pedestrian's states is given by a classical Newtonian mechanics equation with precise environmental information such as distances, speeds, and directions. Schadschneider et al. [5,46] introduced the concept of a floor field which is modified by the presence of pedestrians and obstacles. This allows the cellular automation model to take interactions between pedestrians and the geometry of the system into account in a unified and simple way. The floor field modifies the transition probabilities in such a way that a motion into the direction of larger fields is preferred. Antonini et al. [1] adopted the concept of 'utility' borrowed from economics to quantify the interactions between the decision maker and the other pedestrians in the scene as well as the dynamic aspects of the decision maker itself. The utility values of alternatives are then transformed into probabilities and each pedestrian's movement is randomly selected according to these probabilities.

From a review of previous work, we noticed that these microscopic models are presented based on the promise that precise values of the complex interactions with surrounding environments such as speeds, directions and distances can be used in real time. The environmental effects on a pedestrian's behaviors are evaluated quantitatively based on these precise environmental data. Actually, the information got from environments is perception-based information rather than measurement-based information in most situation. It is difficult to quantify the size of environmental stimuli in real-life scenarios because a pedestrian's perceptions in a specific environment vary from one individual to another, and they are subjective in nature. Individuals have diverse perceptions when they are confronted with environmental interactions, and they may react subjectively to similar situations [14,23,43,64]. Moreover, the inter-relationship between pedestrian's dynamical behavior and pedestrian's perception toward the surrounding environment is rarely considered in previous studies. The perception-based information is often neglected in this area of researches. As such, the urgency underlying the current study is to develop a useful model which can make full use of perception-based information and capture the relationship between the environmental design and the pedestrian's perception.

To meet these goals, we employ a fuzzy logic approach in this study. The theory of fuzzy logic systems, inspired by the remarkable human capability, possesses the capability of operating on and reasoning with perception-based information [62–64]. Consider the intrinsic limitations of humans' cognitive abilities for distinguishing detail and storing information, pedestrian's perceptions toward surrounding environments are usually represented by natural language, which are inherently vague and imprecise. A fuzzy logic approach, compared with other methods, is highly robust in coping with the uncertainty and imprecision that are inherent in perception information. It also provides a scientific approach for the management of pervasive reality of fuzziness and vagueness in human cognition [63]. In addition, fuzzy logic also has the ability to utilize human experience and knowledge and imitate human thought processes [32]. For example, the near obstacle has a greater impact on the obstacle-avoiding behavior than the far. Using the fuzzy logic framework, the processes of pedestrian's reasoning and decision making can be formulated by a set of simple and intuitive fuzzy rules, coupled with advantages of accessible input information and easily understandable output [62].

The novelty of this study is the proposing of the fuzzy logic based pedestrian model, which can incorporate efficiently human experience and knowledge and pedestrian's perceptions toward surrounding environments into the modeling process. The main contribution of this paper are briefly summarized as follows: (i) A fuzzy logic-based microscopic pedestrian

Table 1
Summary of typical microscopic pedestrian behavior models and their characteristics.

Typical model	Study	Space and time	Environmental factors	Specific medium	Typical phenomena
Social force model	Helbing et al. [18,20] Wan et al. [51]	Continuous	Pedestrians Wall Exit	Physical force	Clogging Faster-is-slower Lane formation Oscillatory change
Cellular automata model	Burstedde et al. [5] Schadschneider [46] Fu et al. [13]	Discrete	Pedestrians Obstacle Exit	Floor field	Clogging Lane formation
Lattice gas model	Muramatsu et al. [38] Tajima et al. [48]	Discrete	Walkers Wall Exit	Drift/Bias	Jamming Lane formation
Discrete choice model	Antonini et al. [1] Lovreglio et al. [30]	Discrete	Pedestrian Obstacle Destination	Utility	Free flow Exit selection
Agent-based model	Pan et al. [41] Tan el al [49]	Continuous/ Discrete	Agent Group Obstacle Exit	Rule	Competitive behavior Queuing behavior Herding behavior
Game theoretic model	Lo et al. [29] Bouzat et al. [4]	Continuous	Agent Wall Target	Payoff	Clogging Exit selection

model is proposed to simulate pedestrian dynamic behaviors. The model differs from other models in that it can take full advantage of human experience and knowledge and perceptual information obtained from interaction with surrounding environments, which are widely available and extremely useful, and often neglected in this area of researches. (ii) The effects of complex interactions with surrounding environments on pedestrian dynamics are considered qualitatively during the modeling process. The model describes different influences affecting individual pedestrian motions by a few simple fuzzy logic rules. The local obstacle-avoiding behavior, regional path-searching behavior and global goal-seeking behavior are modeled as fuzzy inference systems with predefined input and output variables. These behaviors are adopted to guide pedestrians to avoid the front obstacles, select the lowest negative energy path, and move in direction of their goals, respectively. At each step, the decisions of turning angle and movement speed are determined by the integration of intermediate results of three behaviors with the weighted average method. (iii) Weighting's assignment principles are designed to adjust weighting factors of three behaviors automatically rather than assign arbitrary fixed values in advance. This enables a pedestrian to avoid potential conflicts and make reasonable decisions in complex situations. (iv) The characteristics of three common crowd organization forms, i.e. crowd evacuation, unidirectional and bidirectional pedestrian flows, are investigated by using the fuzzy logic model. Self-organization phenomena, including 'arching and clogging', 'faster-is-slower effect' and 'lane formation', are reproduced by simulations of the proposed model. The fundamental diagrams of speed-density and density-flow are also investigated in a quantitative way. It is expected to be useful to the exit and hallway design of buildings. (v) The effects of walking habits on the traffic efficiency of bidirectional pedestrian flows are also performed.

The organization of this paper is as follows: Section 2 provides an overview of related works. In Section 3, the architecture of the proposed fuzzy logic model is presented. The detailed implementation methods of the local obstacle-avoiding behavior, regional path-searching behavior, global goal-seeking behavior, and weighting's assignment principle are described in this section; The validation and simulation of the proposed model are discussed in Section 4; Finally, Section 5 concludes the paper with remarks for future works.

2. Related works

2.1. Background of microscopic pedestrian behavior models

Over the years, researchers have constructed various microscopic models to approximate and simulate pedestrian dynamical behaviors in normal and panic scenarios. Examples of microscopic models are the social force model [18,20,51], cellular automata model [5,13,46], lattice gas model [38,48], discrete choice model [1,30], agent-based model [41], and game theoretic model [4,29], which have been proposed to investigate characteristics of crowd evacuation, bidirectional pedestrian flows, crossing pedestrian flows, exit selection and so on, and further to guide the architectural design. Some wonderful results such as 'clogging' [18,20,29], 'faster-is-slower' [18,20], 'lame formation' [5,18,20,38,46,48], 'oscillatory change' [18,20], and 'herding behavior' [41] have been found with simulations of these models. The summary of typical microscopic pedestrian behavior models and their characteristics are shown in Table 1. Each of the typical models mentioned in Table 1 has its own advantages and weaknesses. Based on the specific requirements and simulation scenario, one model can be more suitable than the others.

The social force model [18,20,51] treats pedestrians as particles driven by the resultant force of self-driven force, interaction force with pedestrians, and interaction force with walls. The factors such as distances, speeds, and directions are considered to determine the accelerated velocity of next step. However, its computational complexity rises with the square of the number of pedestrians. Moreover, it is difficult to capture real behavioral rules in a slightly more complex scenario. For the cellular automata model [5,13,46], the physical space is represented by a regular grid composed of cells. Each cell can be in two states, occupied or unoccupied. At each time step, the state of each cell is updated based on previous states of itself and its immediate neighbors. The floor field is introduced to model the longer-ranged interactions with environment such as obstacle and exit. The simplicity of transition rules makes this model more efficiency and allows it to be used for simulations of very large crowds. But, pedestrians can only walk inside or at the grids which is not corresponding to the reality. In addition, tracking total amount of travel time and distance accurately are difficult because of the discrete nature of space and time. As a special case of cellular automata model, the lattice gas model [38,48] treats pedestrian as an active particle on the grid. Since the lattice gas models is conceptually simpler and can be easily implemented on computers for numerical investigations, it has found wider applications in simulating the counter channel flow and bottleneck flow. But, the lattice gas model and the cellular automaton model suffered from similar infirmities. As the representative of local discretization, discrete choice model [1,30] uses a dynamic and individual-based spatial discretization representing the local space in front of pedestrians. It interprets the pedestrian walking process as a sequence of choices over time. The first step is to judge which behavioral pattern will be adopt in the next time step according to individual's current environment, and then to judge which computing methodology of utility is selected under a certain behavioral pattern. Then, two different model formulations are used to determine the choosing probability of each alternative. Nevertheless, the difficulties of this model are parameters calibration and utility computation. The agent-based model [41] proposes a computational methodology that pedestrians are modeled as autonomous agents, which are capable of interacting with each other. At a microscopic level, the framework represents human individuals as autonomous agents equipped with sensors, decision-making rules, and actuators. At a macroscopic level, it models human social behaviors as emergent phenomena through simulating the interactions among agents or groups in a virtual environment. Although the agent-based model can reappear many real behaviors of pedestrians, it is not fully validated as a pedestrian model. Meanwhile, the fundamental diagrams of speed, density, and flow are difficult to investigate in a quantitative way. The game theoretic model [4,29] is proposed based on the premise that the interactive decision processes of crowds are rational. In a game, the agents assess all of the available options and select the alternative that maximizes their utility, and the final utility payoff of each agent depends on the profile of courses of action chosen by all agents. Actually, the decision making of a pedestrian is not absolute rational in many scenarios, especially in panic.

Based on the above discussion, we propose a fuzzy logic model that takes human experience and knowledge into full consideration in modeling process. Then we associate the perceptual information obtained from environment with the decision making of pedestrian's behaviors. The environmental effects on pedestrian dynamic behavior are evaluated qualitatively based on a series of fuzzy logic rules. Our goal is to devise a realistic model that is able to model and predict pedestrian's behaviors in normal and emergency situations. The modeling process is presented in detail in the following section.

2.2. Related research on fuzzy logic and its applications

Understanding how an individual's perception toward the surrounding environment affects modeling of pedestrian dynamic behaviors is a critical step toward a more reliable description of pedestrian flows in real-life situations. Researchers have made many efforts to evaluate the effects of environmental perception on pedestrian's wayfinding [23,43], displacement/locomotion [31,59], and steering behavior [39,40] from different perspectives. In general, the perceptual information is described by natural language because of the intrinsic limitations of humans' cognitive abilities for distinguishing details and storing information. Fortunately, humans have outstanding ability of computing and reasoning with imprecise information instead of exactly numerical value, arriving at reasonable conclusions expressed as words from premises expressed in a natural language or having the form of mental perceptions. For example, backing a truck to a loading dock is a complex nonlinear control problem. It is difficult to model this process mathematically. But skilled drivers can accomplish this task easily by their heuristic experience without any accurate measurement and calculation. They do not necessarily know the more concrete information of steering wheel angle and position of accelerator but imprecise and incomplete information such as 'big', 'small', and 'Middle'. Fuzzy sets theory proposed by Zadeh [61] provides a useful tool to model and characterize the imprecision and uncertainty of perceptual information. This theory has been rapidly developed since it was put forward. It has been widely used in decision making [28], pattern recognition [9], fuzzy control [8,33,34,67] and so on. It's worth mentioning that besides the fields enumerated above, another fontal and crucial field is the complex systems, which has made many achievements in modeling, analysis, control and evaluation of complex systems [35,52–55,62].

Fuzzy logic, as an extension of fuzzy set theory and an approximate reasoning methodology, possesses the capability of computing and reasoning with perception-based information. It also provides a scientific approach for the management of pervasive reality of fuzziness and vagueness in human cognition [63]. In addition, fuzzy logic also has the ability to utilize human experience and knowledge and imitate human thought processes [32]. During the past five decades, fuzzy logic has found numerous applications in fields of finance [16], industry [65] control [33], and robotics [6,7] etc. It is worth mentioning that fuzzy logic based modeling and simulation have been implemented successfully in robot navigation. Seraji et al. [47] presented a behavior-based navigation model for field mobile robot, using a fuzzy logic approach. A fuzzy navigation strategy was generated lies in the ability to extract heuristic rules from human experience and to obviate the need for an analytical model of the process. Zhu et al. [68] built a fuzzy logic system with 48 fuzzy rules based on the human experience and knowledge, and then made the behavior-based mobile robot to achieve target seeking, obstacle avoidance and barrier following in dynamic environments with uncertainties. Wang et al. [56] addressed the fuzzy logic approach to implement the behavior design and coordination, and ultimately realized real-time robot navigation in unknown environments with dead ends.

Similarly, for the problems relate to modeling and simulation of pedestrian's behaviors, a fuzzy logic approach also has certain advantages over other approaches, such as its ability to use perceptual information, utilize human experience and knowledge and imitate human thought processes. So, it is a natural and suitable tool to model pedestrian dynamic behaviors. Some studies have been carried out to apply a fuzzy logic approach to model and analyze certain pedestrian's behaviors such as steering behavior and crowd evacuation behavior. Haciomeroglu et al. [17] studied the group-based movement of a large proportion of pedestrians in an urban environment by using the fuzzy logic approach. Three fuzzy logic engines are designed for maintaining inter-persona distances, achieving the desired speed, and maintaining the distance to a sub-group, respectively. The approach was shown to adhere to the average speed of pedestrians in groups and the distance between members in the groups. Li et al. [27] introduced a new approach, which integrated fuzzy logic with a data-driven method, to study crowd behaviors. The modified algorithm is adopt to extract fuzzy behavior rules from the state-action samples obtained from crowd videos. Mauro et al. [11] proposed a fuzzy logic-based behavioral model for crowd evacuation, which incorporates the fuzzy perception and anxiety embedded in human reasoning. Some of fuzzy inference system are built to provide the direction of motion, delay in egress, and choice of exit. Nasir et al. [39] proposed a genetic fuzzy system to model and simulate a pedestrian's steering behavior in a built environments. The fuzzy-based model was built to infer the degree of turning angle according to the pedestrian's perception of environmental effects of three future positions as its input. Nasir et al. [40] further investigated same question through built environments under normal, non-panic conditions. The information of environmental influence and imprecise and subjective perception from environment stimuli were taken as the inputs of fuzzy logic model to determine the walking path of a pedestrian. The main difference is that a real walking trajectories data was collected to validate the fuzzy-based model.

Although some positive results for pedestrian dynamics have been achieved by using a fuzzy logic approach, each of them was usually only applied to a given scenario such as a building environment [39,40], urban environments [16] or panic situations [11]. A general model has not been proposed for the description and prediction of different pedestrians' behaviors in different scenarios. And the effectiveness of these models haven't been fully validated in the past studies. The arm of this paper is to consider the use of fuzzy logic for modeling and simulation of pedestrian dynamic behaviors in different scenarios. The proposed model can take human experience and knowledge into full consideration in modeling processes, and associate the perceptual information obtained from environments with the decision making of pedestrian's behaviors. The environmental influences on pedestrian dynamics are evaluated quantitatively based on the obtained perceptual information. Finally, the fuzzy logic model is fully validated by simulations of crowd evacuation, unidirectional and bidirectional pedestrian flows.

3. Model description

In this section, we first introduce a method of representation of physical space which plays a central role in the modeling and simulations. Then, we present the architecture and elements of the fuzzy logic-based pedestrian model. Pedestrian dynamic behaviors are determined by integration of local obstacle-avoiding behavior, regional path-searching behavior and global goal-seeking behavior with mutable weighting factors at three different scopes. Three elementary behaviors and the weighting's assignment principle are modeled as fuzzy inference systems with predefined input and output variables.

3.1. Representation of space

The representation of physical space plays a crucial role in the modeling and simulation of pedestrian dynamic behaviors. In general, there are three most commonly used space representation methods, i.e., grid and individual-specific discretization, radial and individual-specific discretization, and network-based representation [2]. A grid and individual-specific discretization is a static method, which divides the physical space into a grid of cells with a dimension of 10–80 cm [5,46]. Each pedestrian occupies one or more cells, depending on the sizes of cell and body. The recommendations of next step are determined by goal information and local interactions of cells. Contrary to the static representation, a radial and individual-specific discretization is a dynamical representation method. The space is divided into sectors originating at the individual locations, which varies with time and is different for each pedestrian in a scenario [1]. The motion states are ascertained by what a pedestrian actually perceives in each sector. The network-based representation is a completely different approach [3]. The space is consist of links and nodes which represent the key points such as street and entry point or departure point, respectively. The pedestrian can capture strategic decisions even before being in a scene, like route choice and goal seeking. In this study, we adopt a radial-based method for representation of space. Its sample chart is shown in Fig. 1. Pedestrians are seen as a points or particles in a 2D environment with the radius of r_n. Each pedestrian n is characterized by its current position p_n. The behavior variables are defined as the current direction θ_n and current speed V_n. The default maximum value of visual distance $d_{\max}$ and visual angle $2\phi^\circ$ determine the shape and size of a pedestrian's visual field (VF), as shown in the blue shaded area of Fig. 1A [37]. From current position $P_n(x_n, y_n)$ of the decision maker, a goal (the purple dot), which represents the place where pedestrians want to reach, lies in the 'goal angle' γ_g at a 'goal distance' d_g. The angle between current direction and goal direction (current position point to goal point) is denoted as the 'goal angle', as well as the distance between current position point and goal point as 'goal distance'. As shown in Fig. 1B, the visual field of a pedestrian n is divided into five sectors by the radial-based representation method. These sectors are marked as left (l), front left (fl), front (f), front right (fr), right (r), and occupied the central angles of 40°, 30°, 30°, 30°, and 40° from

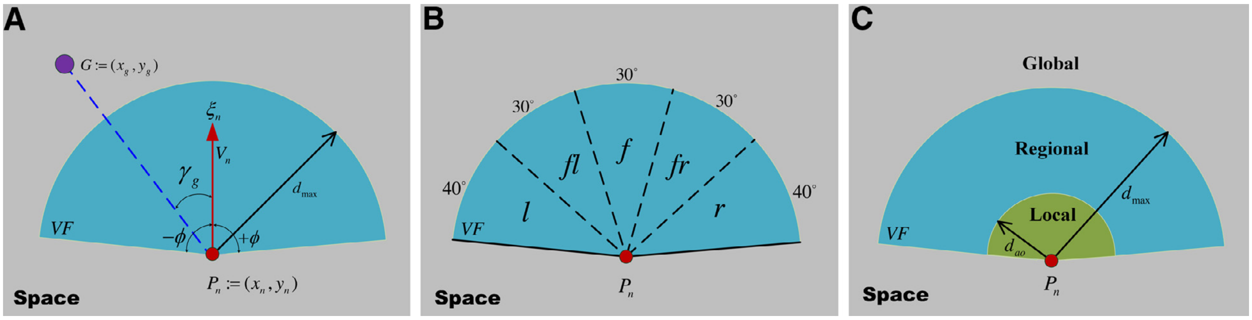

Fig. 1. The sample chart of space representation. (A.) Definition of variables in the descartes rectangular coordinate system: heading direction (ξ_n), movement speed (V_n), goal angle (γ_g), goal distance (d_g), visual angle ($2\phi°$), and horizon distance ($d_{\max}$). (B.) Discretization of space based on 5 radial directions, i.e., left (l), front left (fl), front (f), front right (fr), and right (r) from left to right, respectively. (C.) Three different scopes of influence for elementary behaviors, i.e. local, regional and global scope for obstacle-avoiding behavior, path-searching behavior and goal-seeking behavior, respectively.

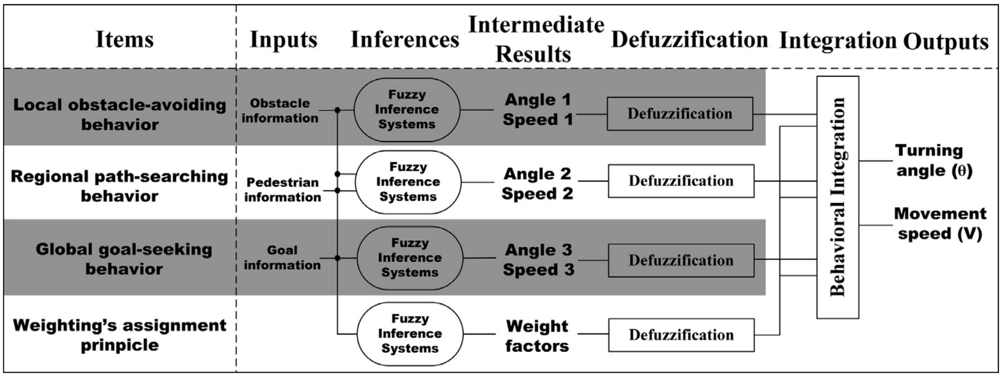

Fig. 2. The overall structure of fuzzy logic based pedestrian model. It mainly consists of five components: inputs, fuzzy inference systems, defuzzification, integration and outputs.

left to right, respectively. A pedestrian can determine his/her movement direction and speed of next step according to what they actually perceived from predefined five sectors. Fig. 1C shows three scopes of space: local (green shaded area), regional (blue shaded area) and global (gray shaded area) scope, which are used to ascertain the affected scopes of obstacle-avoiding behavior, path-searching behavior and goal-seeking behavior, respectively. These mean that the obstacle-avoiding behavior is only affected by objects located in the local scope as well as other two behaviors. It is also shown that there exist inclusion relations between three scopes, i.e. $Local \subseteq Regional \subseteq Global$. In general, obstacles which are far away from the decision maker have little effect on the obstacle-avoiding behavior. Based on previous observations and researches, when an obstacle appeared in the visual field of the decision maker, he/she might not react immediately to avoiding possible collision until the distance between them is less than a certain value [36]. Through synthetical analysis, $d_{ao} = 3m$ is considered as a suitable value.

How to define the concept of visual field is a key problem in representation of physical space. Antonini et al. proposed that visual field is a sector domain with visual angle (170°) in front of the pedestrian, namely the region he/she can actually see [1]. Another definition was presented by Moussaïd et al. [37], that is “the vision field of pedestrian n ranges to the left and to the right by ϕ with respect to the line of sight $\vec{H}_n$”. In addition, it was also defined by Tan et al. by casting laser rays from the eye position of an agent within a visual angle (e.g., 170°) and visual distance (e.g., 10 m) [49]. All these showed that the size of visual field is mainly determined by visual angle and the ‘horizon distance’ $d_{\max}$. $d_{\max}$ and $2\phi°$ represent the maximum perceptual distance and visual angle of the decision maker, respectively. The definition of visual field used in this study is similar with Moussaïd et al. and Tan et al. [37,49]. For simplicity, we have arbitrarily selected $d_{\max} = 8\ m$ and $2\phi = 170°$.

3.2. The fuzzy logic based pedestrian model

Pedestrian dynamics are determined by integration of three elementary behaviors, i.e. local obstacle-avoiding, regional path-searching and global goal-seeking with mutable weighting factors at three different scopes. The overall structure of this model is shown in Fig. 2. A pedestrian is guided to avoid the front obstacles and select the lowest negative energy path by local obstacle-avoiding behavior and regional path-searching behavior, respectively. The global goal-seeking behavior makes a pedestrian has a tendency of moving in direction of his/her goal regardless of external environments. The weighting's

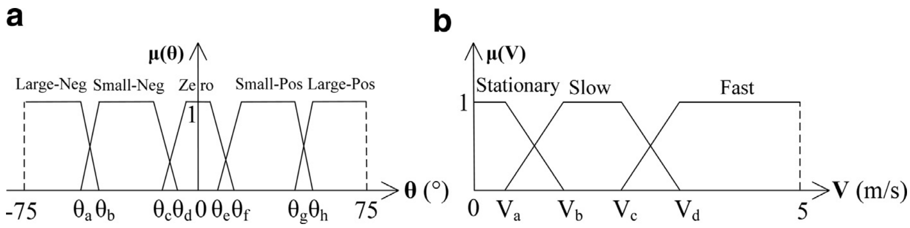

Fig. 3. Membership functions for (a) turning angle, and (b) movement speed.

assignment principle is proposed to integrate multiple behaviors and resolve potential conflicts. All four items are modeled as fuzzy inference systems with the input information of a pedestrian's perception toward surrounding environments, which have greater impact on final decision behaviors. For local obstacle-avoiding behavior, the major factor that strongly affects the decision is the distance between the decision maker and the closest obstacle in each of the predefined sectors. We can use a fuzzy inference system to establish the relationship between a pedestrian's decision and perceived distance information. The similar approach is adopted for the other three items. The final recommendations of turning angle α and movement speed V are obtained by integration of outputs of three elementary behaviors with mutable weighting factors. The magnitudes of weighting factors are adjusted automatically to coordinate three elementary behaviors. For example, IF the distance between the position of decision maker and goal point is considerably large then the position of nearest obstacle, THEN the weighting factors of local obstacle-avoiding behavior is set as 'large', regional path-searching behavior as 'normal', and global goal-seeking as 'small'. The turning angle α is represented by the five linguistic fuzzy sets {Large-Neg, Small-Neg, Zero, Small-Pos, Large-Pos}, with the trapezoidal membership functions shown in Fig. 3(a), where 'Neg' and 'Pos' turn a pedestrian to left and right directions, respectively. Similarly, the movement speed V is represented by the three linguistic fuzzy sets {Stationary, Slow, Fast}, with the trapezoidal membership functions shown in Fig. 3(b). The values of universe of discourse of turning angle and movement speed in Fig. 3(a) and (b) are defined as intervals of $[-75^\circ, 75^\circ]$ and [0 m/s, 5 m/s], respectively.

The number of linguistic fuzzy sets, which are used to cover the discourse of universe of antecedents and consequents, decides the accuracy of fuzzy logic systems. For a certain structural model, the time complexity rises exponentially as the number of input fuzzy sets increases. In this study, we choose two, three, or five fuzzy sets to represent input and output variables in order to trade-off the computing efficiency and accuracy.

3.2.1. Model assumptions

The following reasonable model assumptions related to modeling and simulations of pedestrian dynamic behaviors are made in order to simplify and articulate the proposed model.

- The modeling and simulations are done under normal crowd density in this paper, so pedestrian dynamics are mainly determined by heuristic-based walking behavior rather than physical interactions [37].
- Pedestrians abide by the same rule set in a simulation.
- A pedestrian is characteristic as a circle of radius $r_n = 0.25$ m on the horizontal plane (2D) [15].
- The desired speeds of pedestrians follow a Gaussian distributed with mean value 1.34 m/s and standard deviation 0.26 m/s in simulations [10], the degree of memberships are set as $\mu_{fast}(1.34) = 1$ and $\mu_{slow}(1.34) = \mu_{stationary}(1.34) = 0$.
- Pedestrians only aware of regional information in their visual field and the goal details rather than global information of environments.
- The effect of inertia is ignored during the modeling process, i.e. the saltation of speeds is permitted.

3.2.2. The local obstacle-avoiding behavior

The role of local obstacle-avoiding behavior is to make pedestrians avoid front obstacles located in the local scope. In this study, we define obstacles as any corporal objects such as group of people, walls, columns and tables which may delay or block the movement of pedestrians. The local obstacle-avoiding behavior is dominant in the decision process if the distance between decision maker and the closest obstacle is near. Usually, the distance information obtained from the surrounding environment is reflected as perceptual information such as 'about 3 m', 'far' and 'near' in mind, which is imprecise and uncertain in nature.

To effectively utilize these perceptual-based information, a fuzzy inference system is founded to describe this behavior. The closest pedestrian-obstacle distances in five sectors are replaced by d_o^l, d_o^{fl}, d_o^f, d_o^{fr} and d_o^r from left to right, respectively. If there is no obstacle appeared in one of these sectors, the distance of this sector is set as d_{ao}. The distance is represented by the three linguistic fuzzy sets {Very-Near, Near, Far}, with the trapezoidal membership functions shown in Fig. 4(a). The rule sets for ascertaining the turning angle and movement speed of local obstacle-avoiding behavior are discussed in this section.

We propose a two layers fuzzy inference system to reduce the number of rules and the computational complexity. In the first layer, we search the farthest distance sector in the whole left and right regions independently with a preference toward

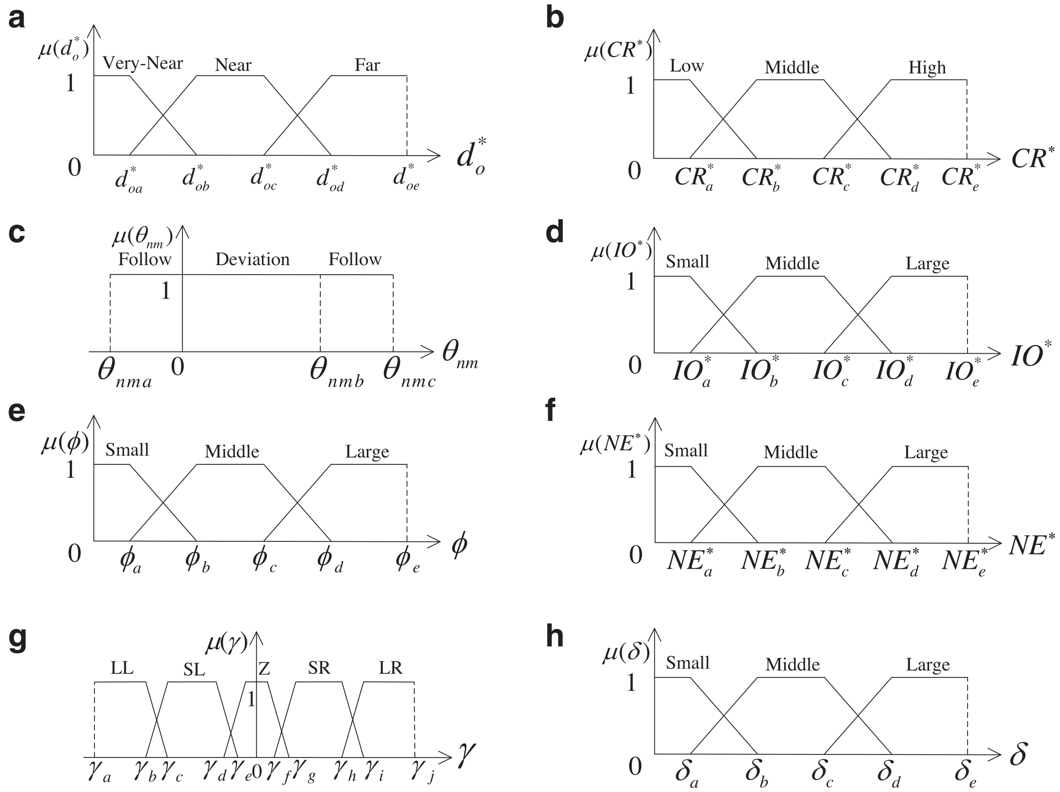

Fig. 4. Membership functions for (a) the closest pedestrian-obstacle distances, (b) collision risk, (c) angles between decision maker and pedestrians, (d) influence of obstacles. (e) angles occupied by obstacles, (f) negative energy, (g) goal angle, and (h) weighting factors.

Table 2
Inference rule set for selecting preferred-left sector.

d_o^l	d_o^{fl}		
	F	N	VN
F	SN	LN	LN
N	SN	SN	LN
VN	SN	SN	SN

the front direction. The whole left sector includes the left sector and front left sector, as well as the whole right sector. In the second layer, we determine the best sector among the preferred left, preferred right, and front sectors. The inference rules of the first layer for turning angle are summarized in Table 2 which are used to find the preferred left sector and the nearest pedestrian-obstacle distance d_o^{pr}, where LN is an abbreviation of 'Large-Neg' and SN is 'Small-Neg'. For example, the (1, 3) element of top layer in Table 2 can be written out as IF d_o^l is 'Far' AND d_o^{fl} is 'Very-Near', THEN α_l is 'Large-Neg'. The bottom left corner of Table 2 can be written out as IF d_o^l is less than or equal to d_o^{fl}, THEN α_l is 'Small-Neg'. The rules reflect the empirical evidence that pedestrians tend to select the direction closest to the current direction (front sector) so that they do not make unnecessary rotation [37]. A similar fuzzy inference system can be constructed for the right regions by replacing *l* and *N* by *r* and *P*. The outputs of the first layer are the preferred turning angles associated with the preferred left (*PL*) and preferred right (*PR*) sectors. The turning rules for the second layer are shown in Table 3, where *UNC* and *Z* stand for 'Uncertainty' and 'Zero', respectively. Note that when the distance d_o^f is 'far', i.e., the left part of the Table 3, the decision maker is dominated to walk along the current direction until he/she faced a front obstacle. If the distances in each sector are the same, the front sector would be chosen as the walking direction. Notice that the first line of middle part and right part in Table 3, when a pedestrian meets the same circumstances of PL and PR sectors, i.e., the values of d_o^{pl} and d_o^{pr} are the same, the recommendation of turning angle is *UNC*. It has the following expression:

$$UNC = \begin{cases} PN & (P = K_s) \\ PP & (P = 1 - K_s) \end{cases} \tag{1}$$

Table 3
Turning rule set of local obstacle-avoiding behavior.

Input			Output	Input			Output	Input			Output
d_o^f	d_o^{pl}	d_o^{pr}	α_1	d_o^f	d_o^{pl}	d_o^{pr}	α_1	d_o^f	d_o^{pl}	d_o^{pr}	α_1
F	F	F	Z	N	F	F	UNC	VN	F	F	UNC
F	F	N	Z	N	F	N	PP	VN	F	N	PP
F	F	VN	Z	N	F	VN	PP	VN	F	VN	PP
F	N	F	Z	N	N	F	PN	VN	N	F	PN
F	N	N	Z	N	N	N	Z	VN	N	N	UNC
F	N	VN	Z	N	N	VN	Z	VN	N	VN	PN
F	VN	F	Z	N	VN	F	PN	VN	VN	F	PN
F	VN	N	Z	N	VN	N	Z	VN	VN	N	PN
F	VN	VN	Z	N	VN	VN	Z	VN	VN	VN	Z

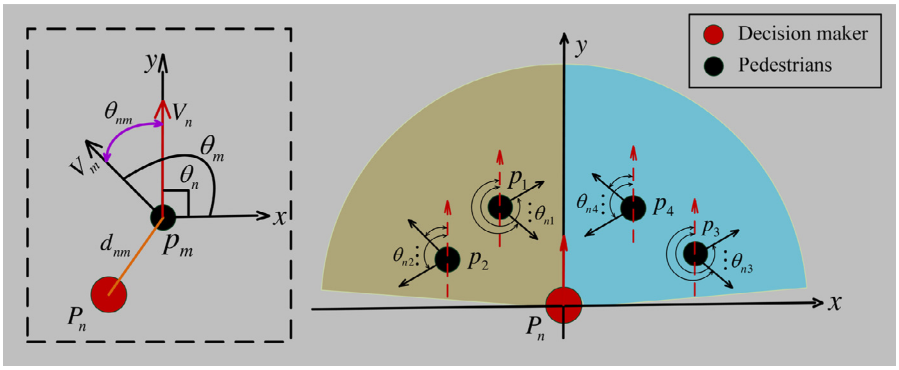

Fig. 5. Illustration of the decision maker P_n facing nearby pedestrians.

where $K_s \in [0, 1]$, the *PN* is selected with a probability of K_s, as well as *PP* with a probability of $1 - K_s$. The selection probability K_s mainly depends on people's living habits. For example, the Chinese people have a tendency to walk on the right side of the road, while the Japanese are just the opposite. So the probability K_s is usually larger than 0.5 in China and smaller than 0.5 in Japan [26]. The advantage of using *UNC*, over choosing either left or right sector arbitrary, is that it offers pedestrians a selection to reduce subjective biases.

The recommendation of a pedestrian's speed for the local obstacle-avoiding behavior is determined by the closest pedestrian-obstacle distance in front sector, i.e. d_f. We can use three fuzzy logic rules to describe the speed choosing strategies.

(1) IF d_o^f is Very-Near, THEN V_1 is Stationary;
(2) IF d_o^f is Near, THEN V_1 is Slow;
(3) IF d_o^f is Far, THEN V_1 is Fast.

The decision maker will slow speed or even stop suddenly when facing a front obstacle at the local scope, whereas, he/she will walk freely with desired speed.

3.2.3. The regional path-searching behavior

This section analyzes the modeling process of the regional path-searching behavior which drives a pedestrian to the safest path in the regional scope (i.e. the visual field). A fuzzy inference system, as shown in Fig. 2, is constructed to describe this behavior. The concept of negative energy (NE) is defined to evaluate the degree of safety. Its value depends on the distribution of pedestrians and obstacles which appeared in the visual field of the decision maker. We use the collision risk (CR) and influence of obstacle (IO) to characterize the energy produced by pedestrians and obstacles, respectively. The speeds of front pedestrians, and the angles and distances between pedestrians and the decision maker are considered as the dominant factors of the CR. The size of IO is determined jointly by the visual angle occupied by obstacles and closest pedestrian-obstacle distance. With a manner similar to the local obstacle-avoiding behavior, the final turning angle is determined by the values of NE in five sectors. The speed is determined by the NE of the front sector.

(a) Collision risk assessment: In this study, collision risk is defined as the possibility of a collision with the neighbors who appeared in the visual field of the decision maker. CR is represented by three linguistic fuzzy sets {Low, Middle, High}, with the membership functions shown in Fig. 4(b). It is determined by the variables of θ_{nm}, d_{nm}, and V_m. They are illustrated in the left part of Fig. 5, where d_{nm} is the distance between the decision maker P_n and a nearby

Table 4
Collision risk assessment rules R_1 for a moving pedestrian.

Input			Output	Input			Output
θ^*_{nm}	V^*_m	d^*_{nm}	CR^*_m	θ^*_{nm}	V^*_m	d^*_{nm}	CR^*_m
A	Fast	VN	H	D	Fast	VN	L
A	Fast	N	H	D	Fast	N	L
A	Fast	F	H	D	Fast	F	L
A	Slow	VN	H	D	Slow	VN	L
A	Slow	N	M	D	Slow	N	L
A	Slow	F	M	D	Slow	F	L

moving pedestrian p_m in the visual field, V_n and V_m are the speed of P_n and p_m, respectively. θ_{nm} is defined as the angle between the movement direction of a pedestrian m and the decision maker n:

$$\theta_{nm} = \theta_m - \theta_n, \ \theta_n = 90^\circ, \ \theta_m \in (0^\circ, 360^\circ] \tag{2}$$

where θ_n and θ_m are angles from x-axis to movement directions, turning in a counterclockwise direction. The effects of d_{nm} and V_m on CR should be obvious. But, the effect of θ_{nm} is relatively complex. For example, a pedestrian appeared in the left or right part of visual field with same angle θ_{nm} brings different degree of risk to the decision maker. The assessment rule follows a basic rule of thumb that a pedestrian who walks toward the decision maker P_n brings more risk than deviates from P_n.

To illustrate, the left-hand side of Fig. 5 shows four pedestrians with same values of speed V_m and distance d_{nm}, who located in the left part and pointing to the right half of the plain (P_1), in the left and pointing to left half of the plain (P_2), in the right and pointing to right half of the plain (P_3) and in the right and pointing to left half of the plain (P_4), respectively. The range of angles are $\theta_{n1}, \theta_{n3} \in [180^\circ, 270^\circ] \cup [-90^\circ, 0^\circ]$ and θ_{n2}, $\theta_{n4} \in [0^\circ, 180^\circ)$. Obviously, pedestrians whose moving directions pointing to the decision maker are considered to have large effects on CR, i.e., the pedestrians located in the left side with angle of $\theta_{nm} \in (0^\circ, 180^\circ]$ or in the right side with $\theta_{nm} \in [180^\circ, 270^\circ] \cup [-90^\circ, 0^\circ]$. Conversely, the moving directions deviating from the decision maker have small effects on collision risk. We can see from the right-hand side of Fig. 5 that the size of CR is $P_1 > P_2$ in the yellow region, whereas, it is completely opposite in the blue region, i.e., $P_3 < P_4$. The angle θ_{nm} is represented by the two linguistic fuzzy sets {Approach , Deviation}, with the membership functions shown in Fig. 4(c). The representation of V_m and d_{nm} are same as the movement speed V and closest pedestrian-obstacle distance d^*_o, respectively. In accordance with the above analysis, the rule set of collision risk assessment for a pedestrian is shown in Table 4. Note that the output of system is low when the pedestrian deviated from the decision maker. Conversely, a pedestrian brings high risk if and only if he/she walked toward the decision maker with a big speed or a very near distance. The overall risk for pedestrians in each sector is

$$CR^* = \sum_{m=1,2,\cdots,N} R_1(\theta^*_{nm}, d^*_{nm}, V^*_m) \tag{3}$$

where the asterisk ($*$) indicates one of the five sectors {l, fl, f, fr, r}, N is the total number of pedestrians appeared in this sector.

(b) Analysis the influence of obstacles: Obstacles in the visual field also bring negative energy for the regional path-searching behavior. The impact imposed on the decision maker will differ depending on the visual angle occupied by obstacles and closest distances between decision maker and obstacles, which are denoted by ϕ^*_{oi} and d^*_{oi}, respectively. A schematic of the decision maker facing obstacles is shown in Fig. 6. The obstacles hidden behind the others (i.e. the white grid regions shown in the Fig. 6) have no effect on IO, as well as outlying obstacles (i.e. the blue grid regions shown in Fig. 6), we can ignore these obstacles when analyzing their influences. The size of IO^* is represented by the three linguistic fuzzy sets {Small, Middle, Large}, with the membership functions shown in Fig. 4(d).
As the occupied central angle of each sector is not exactly the same (40°, 30°, 30°, 30° and 40° from left to right), so the domain of discourses of $\phi^*_{oi} (* \in \{l, fl, f, fr, r\})$ are not identical. We convert them to the same interval with a scaling factor. Then the ϕ^*_{oi} are represented by the three linguistic fuzzy sets {Small , Middle, Large}, with the membership functions shown in Fig. 4(e). The rule set for assessment the influence of an obstacle is shown in Table 5, which is derived directly from the occupied visual angle ϕ^*_{oi} and closest distance d^*_{oi}. Observe that two factors are equally important for IO^*. The large the blocked vision angle and the closer the distance, the greater the value of IO^*. The total influence of obstacles in each sector is

$$IO^* = \sum_{i=1,2,\cdots,M} R_2(\phi^*_{oi}, d^*_{oi}) \tag{4}$$

where the definition of asterisk ($*$) is same as above, M is the total number of obstacles appeared in this sector.

(c) Turning rules and movement rules: Negative energy of a sector (NE^*) is produced from the repulsive interactions with obstacles and pedestrians, and it dominates the regional path-searching behavior directly. As illustrated in Fig. 2, its

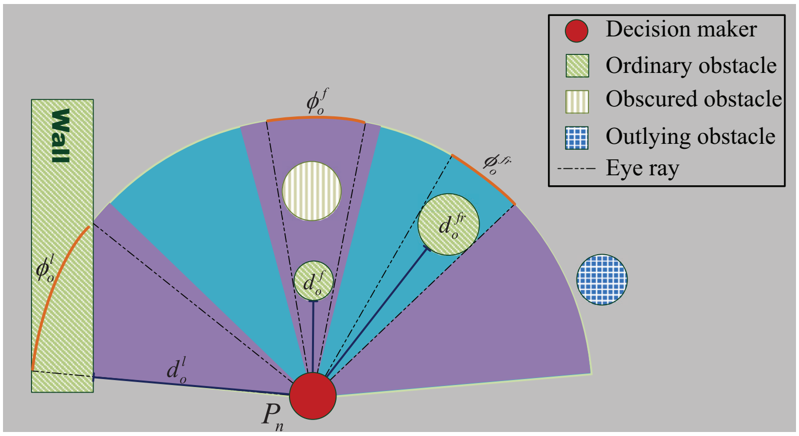

Fig. 6. Illustration of the decision maker P_n facing obstacles. (For interpretation of the references to colour in the text, the reader is referred to the web version of this article.)

Table 5
Inference rules R_2 for influence of an obstacle.

d_{oi}^*	ϕ_{oi}^*		
	S	M	L
F	S	S	M
N	S	M	L
VN	M	L	L

Table 6
Inference rules for negative energy.

CR^*	IO^*		
	L	M	S
H	L	L	M
M	L	M	M
L	M	M	S

effect arises from synergistic interaction between primitive factors, collision risk and influence of obstacles. The rules for evaluating negative energy is shown in Table 6. From this table we can see that the negative energy is 'small' if and only if CR^* and IO^* are all 'low', and it increases obviously until one of them reaches the 'middle' or 'high' level.

We develop a system for the regional path-searching behavior, which is similar with that used to model the local obstacle-avoiding behavior. Negative energy obtained from each of five sectors are replaced by $\{NE^l, NE^{fl}, NE^f, NE^{fr}, NE^r\}$. It is covered by the three linguistic fuzzy sets {Small, Middle, Large} with the membership functions shown in Fig. 4(f). The rule sets are similar to those described in Tables 2 and 3, with d_o^* replaced by NE^* and {Very-Near, Near, Far} replaced by {Small, Middle, Large}. Note that pedestrians always tend to choose the minimum negative energy sector as their preferential path in the region scope.

3.2.4. The global goal-seeking behavior

The goal-seeking behavior is a kind of global behavior which reflects a tendency that pedestrians always move in directions to their goals regardless of external environments [1,37]. The turning angle for global goal-seeking behavior is determined by the goal angle γ_g. We can see from Fig. 1(A) that the range of goal angle is $\gamma_g \in [-75^\circ, 75^\circ]$, and it is represented by five linguistic fuzzy sets {Large-Left, Small-Left, Zero, Small-Right, Large-Right} with the membership functions shown in Fig. 4(g). The turning rules are summarized in Table 7.

Note that once the decision maker deviates from the direction of goal, the turning rules of the global goal-seeking behavior will eventually turn his/her movement direction back toward it.

The following five rules are developed to determine the recommendation of movement speed of the global goal-seeking behavior:

Table 7
Turning rules for the global goal-seeking behavior.

Input γ_g	LL	SL	Z	SR	LR
Output α_3	LP	SP	Z	SN	LN

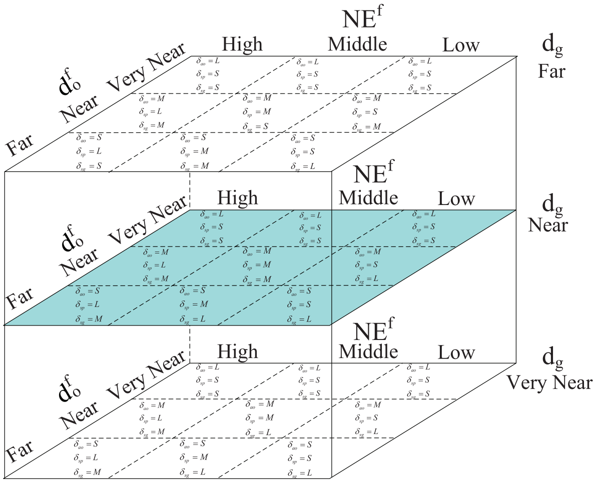

Fig. 7. Weighting's assignment rules for three elementary behaviors.

(1) IF d_g is Far, THEN V_3 is Fast;
(2) IF d_g is Near AND γ_g is Zero, THEN V_3 is Fast;
(3) IF d_g is Near AND γ_g is not Zero, THEN V_3 is Slow;
(4) IF d_g is Very-Near AND γ_g is Zero, THEN V_3 is Fast;
(5) IF d_g is Very-Near AND γ_g is not Zero, THEN V_3 is Stationary.

The 'goal distance' d_g is represented by three linguistic fuzzy sets {Very-Near, Near, Far} with the membership functions shown in Fig. 4(f). The first rule reveals that the decision maker moves freely with desired speed if the value of d_g is big enough. The speed is 'fast' as long as goal angle is 'zero'. But, the speed is 'stationary' when the decision maker is very close to but not facing the goal.

3.2.5. Integration of multiple elementary behaviors and conflict resolution

In the previous sections, the local obstacle-avoiding behavior, the regional path-searching behavior, and the global goal-seeking behavior are described independently for determination of pedestrian's turning angles and movement speeds at three different scopes. Each behavior has different degree of effects on the final decision results in different situations. A conflict occurs if two of these three elementary behaviors give whole contrary recommendations. For example, the local obstacle-avoiding behavior dominates the pedestrian to turn right with a big turning angle, and the regional path-searching behavior dominates to turn opposite direction. The conflict may lead to wrong decision, which will take a pedestrian into region where he/she didn't want (have) to go. There are many strategies such as the degree-of-architecture method [50], context-dependent blending method [44], weighted mean method [56] have been proposed to integrate multiple behaviors and resolve potential conflicts. The integration methodology we employed in this study is the simple weighted mean method [56]. The recommendations of three elementary behaviors are calculated independently by using the fuzzy inference systems proposed above. The weighting factors of these behaviors are adjusted dynamically according to perceptual information obtained from surrounding environments rather than adopted arbitrary fixed values in advance. The values of weighting factors δ_{ao}, δ_{sp}, and δ_{sg} dominate the degree of influence of each behavior on the final results of α and V, where δ_{ao}, δ_{sp}, and δ_{sg} represent the weights of the local obstacle-avoiding behavior, regional path-searching behavior and global goal-seeking behavior, respectively. These weights are represented by the three linguistic fuzzy sets {Small, Middle, Large} with the membership functions shown in Fig. 4(h). The rule set for the weighting's assignment principle is summarized in Fig. 7.

The weighting's assignment rules continuously update the weighting factors of three behaviors to resolve conflicts in response to possible environmental conditions. When a pedestrian faces a safe and obstacle-free environment, the global goal-seeking behavior dominates and drives he/she toward the goal. When a pedestrian faces a cluttered environment, conversely, the weights of local obstacle-avoiding behavior and regional path-searching behavior are increased significantly to avoid the potential collision and get out of the high negative energy region at the expense of deviating from the nominal path to the goal. Observing that the above weighting assignment rules are complete and exhaustively partition the entire space of possibilities.

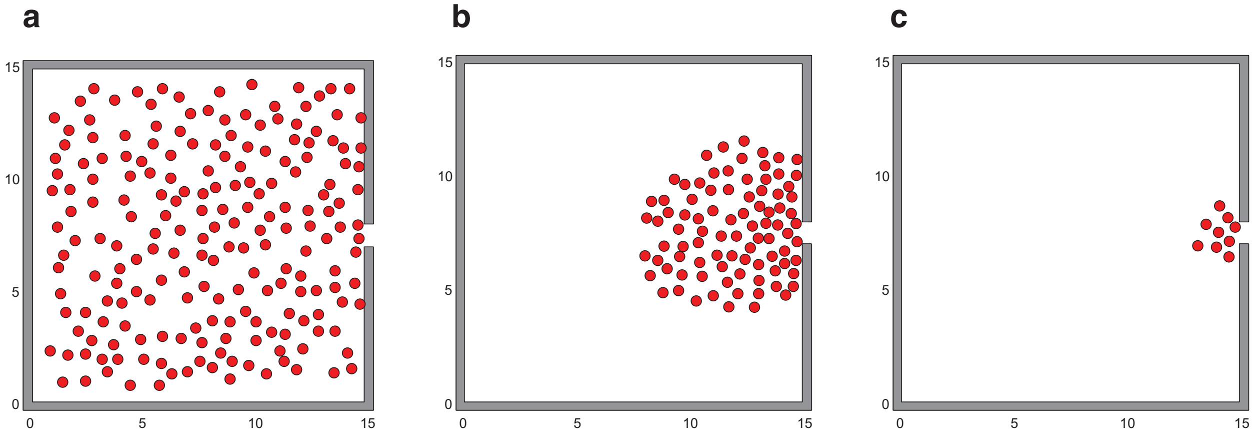

Fig. 8. Snapshots of crowd evacuation: (a) at time step 10, (b) at time step 150, and (c) at time step 250.

The final results of turning angle α and movement speed V are determined by integration of recommendations of obstacle-avoiding behavior, path-searching behavior and goal-seeking behavior with mutable weighting factors by using the weighted average method.

$$\begin{cases} \alpha = \dfrac{\widetilde{\delta}_{ao} \cdot \tilde{\alpha}_1 + \widetilde{\delta}_{sp} \cdot \tilde{\alpha}_2 + \widetilde{\delta}_{sg} \cdot \tilde{\alpha}_3}{\widetilde{\delta}_{ao} + \widetilde{\delta}_{sp} + \widetilde{\delta}_{sg}} \\ V = \dfrac{\widetilde{\delta}_{ao} \cdot \tilde{V}_1 + \widetilde{\delta}_{sp} \cdot \tilde{V}_2 + \widetilde{\delta}_{sg} \cdot \tilde{V}_3}{\widetilde{\delta}_{ao} + \widetilde{\delta}_{sp} + \widetilde{\delta}_{sg}} \end{cases} \tag{5}$$

where~represents the crisp value of the counterpart fuzzy set which is calculated by using the Center-of-Gravity defuzzification method [42]. Three elementary behaviors are mutually coordinated and restrained by the weighting's assignment rules so that pedestrians can arrive at their goals safely with suitable strategies.

4. Simulations and results

Once the fuzzy logic-based pedestrian model has been established, we can use it to predict pedestrian dynamics and then discover crowd's characteristic features and collective phenomena in different scenarios. But before that, the effectiveness of the proposed model must be validated. General methods used to validate the pedestrian models include the computer simulations and controllable real experiments. For the computer simulations, a commonly used strategy is to compare with the well-known collective phenomena or adjust the parameters and components of the models until a similar tendency between the simulation results and the fundamental diagrams are satisfied [58]. For controllable real experiments, the real data collected by cameras or experimenters are used to contrast with model-based simulation results until an acceptable range of the error between them is reached [40].

4.1. Validation of the model

In this study, the time-based computer simulation approach is selected with the time step of $\tau = 0.5$ S*s*. First, we validate the model in the simple evacuation situation. The scenario is a square room of size 15 m $\times$ 15 m with a 1 m wide exit. It is the same as that adopted by Helbing et al. [18]. The exit is located at the middle position of the east wall. Pedestrians are assumed to be scattered in a random positions without overlap between each other. The initial directions and speeds are given at random. Other parameters of this simulation are set as follow: the initial number of pedestrians $N = 200$, the pedestrian's radius $r_p = 0.25$ m, and the desired speeds follow a Gaussian distributed with mean value 1.34 m/s and standard deviation 0.26 m/s [10].

Fig. 8(a)–(c) display the snapshots of crowd evacuation initially with 200 pedestrians ($N = 200$) in the room at time step 10, 150, and 250, respectively. First, all pedestrians walk toward the exit at a desired speed. Then, the arching and clogging of crowd occurs, and only a few pedestrians who approach the exit have enough space through the exit. At last, the remnant part of pedestrians evacuate from the room in an orderly manner. We can observe the generating process of arching crowds and bursting exit behaviors near the exit.

In Fig. 9 we plot the evacuation time T versus pedestrians' desired speed V_p. The simulation results derive from averaging the testing values of repeated simulations with the same model parameters. The following results are got by the same way unless otherwise specified. The pink lines in Fig. 9 is obtained by simulations of the proposed model in the room evacuation scenario with different desired speeds, which shows a similar changing trends with the results of Helbing et al. [18] and

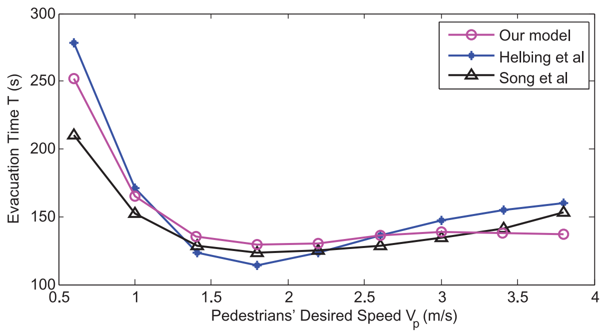

Fig. 9. Evacuation time T versus pedestrians' desired speed V_p contrasting with empirical results.

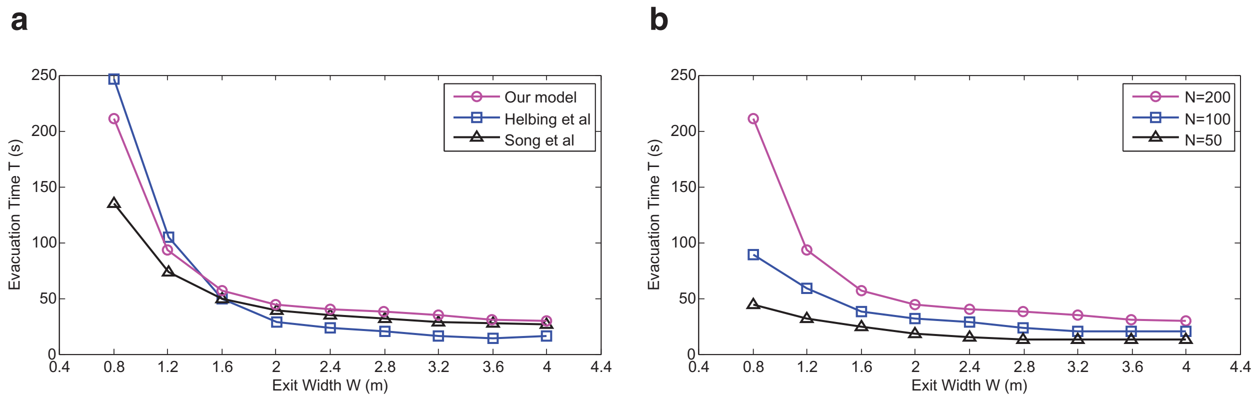

Fig. 10. The influence of exit widths on evacuation times: (a) comparing with empirical results, (b) under different initial densities.

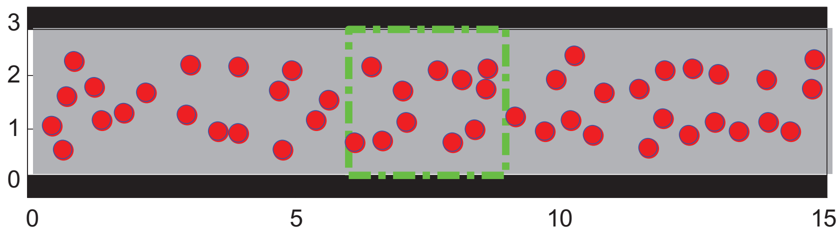

Fig. 11. The hallway scenario used for measuring the average speed and density of a pedestrian. The solid circles represent pedestrians crossing the hallway from the left to the right hand side and reentering the hallway from left-hand boundary once they are quitted from the right-hand boundary.

Song et al. [57]. The evacuation time decreases with growing desired speed when V_p is relatively small. The desired speed higher than 1.5 m/s in turn reduces the evacuation efficiency, which could reflect the effect of 'faster-is-slower' phenomenon [18].

The influence of the exit widths on evacuation times are investigated in the same evacuation scenario. From Fig. 10 (a), the results of comparison with existed works showed that the relation curve obtained by the simulation of fuzzy logic model is almost the same as that by social force model [18] and CAFE model [57]. Evacuation time T decreases nonlinearly as the exit width W increased, eventually reaching a saturation state where further increases in W does not have significant impacts on T. It is shown in Fig. 10 (b) that the variety of crowd density do not affect the inverse-correlative property of curves, but affect the values of evacuation time. The results demonstrated in Fig. 10 can be used to support the design of exit width. A critical size of the exit would be determined if the room size and expected density was given.

Then, we investigate the relationship between speed and density which is known as the fundamental diagram obeyed by pedestrian dynamics. A 3 m $\times$ 15 m hallway scenario with periodic boundary conditions, see Fig. 11, is designed to measure the speed-density relation of unidirectional pedestrian flow. A measurement segment of 3 m $\times$ 3 m representing with green dotted box is set in the middle of the hallway. The global density of the hallway is controlled by adjusting the total number N at initial time, and the number of pedestrians is varied from 20 to 135 in this simulation. A fixed number of pedestrians with random directions and speeds are scattered in the hallway without overlap between each other. Pedestrians cross the hallway from the left to the right hand side, and reenter the hallway from left-hand boundary once they are quitted from

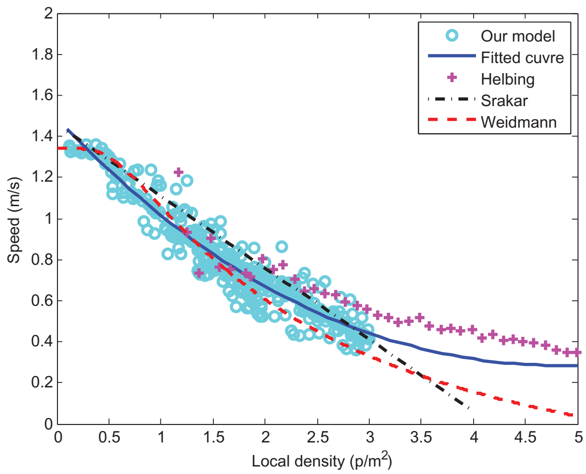

Fig. 12. Measured speed-density relationship contrasting with empirical results.

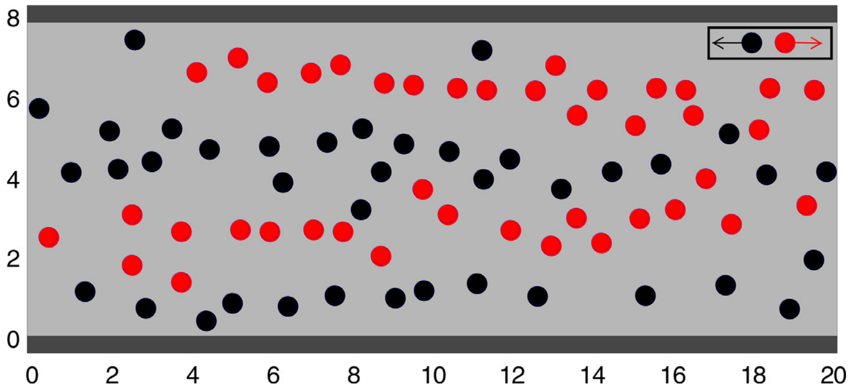

Fig. 13. Typical simulation results for lane formation in bidirectional pedestrian flows through a hallway. The red dots represent pedestrians crossing the hallway from the left to the right hand side which is opposite to that of pedestrians symbolized by black dots. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the right-hand boundary. We use the measurement method proposed in Ref. [10] to obtain the average speed v_n and density ρ_n of a pedestrian n at a time interval.

The results of speed-density relation (bright blue circles) are shown in Fig. 12. The blue line represents the best fitted curve ($R^2 = 0.916$) obtained by using a least squares procedure. It can be find that the tendency of the fundamental diagram is consistent with that derived by the former researchers [19,45,58] at the density domain $0 < \rho < 3$ p/m^2. When the density is below 0.5, pedestrians can move at a desired speed because of the adequate space and slight effects of other pedestrians and obstacles. The average speed decreases obviously with the increase of density. Further, the crowds almost remained stationary when the density exceeds the critical condition.

4.2. Simulations of bidirectional pedestrian flow

As a most common traffic-organization form, the bidirectional pedestrian flow is more complex than unidirectional pedestrian flow because of complicated interactions and head-on conflicts between counter pedestrian. Understanding the characteristics of bidirectional pedestrian flow is very important to improve the efficiency of emergency evacuation and transport infrastructure.

A simulation of bidirectional pedestrian flows is presented in Fig. 13, which shows the results of a simulation with a 8 m wide and 20 m long hallway. Pedestrians enter the hallway at the ends of each side at random positions with the flow of two person per second. Those intending to walk from the left side to the right side are represented by red dots, whereas pedestrians intending to move into the opposite direction are represented by black dots. The value of probability K_s in (1) is set as 0.5. In this simulation, a pedestrian automatically chooses the proper route to avoid collision with others at suitable speed. Sometime later, four dynamic lanes are formed by the pedestrians who intend to walk into the same direction. Our simulation result is in accord with the conclusion of Helbing et al. [20] that the average expected number N_l of lanes emerging on a hallway scales linearly with its width W_h ($N_l(W_h) = 0.36 * W_h + 0.59$). The number of lanes is four

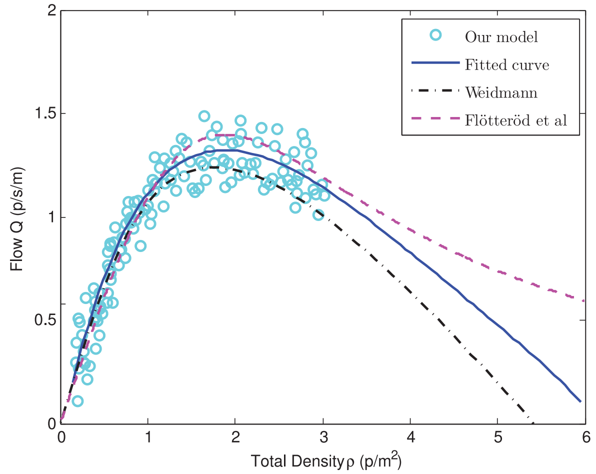

Fig. 14. Measured density-specific flow relationship contrasting with empirical results. (For interpretation of the references to colour in the text, the reader is referred to the web version of this article.)

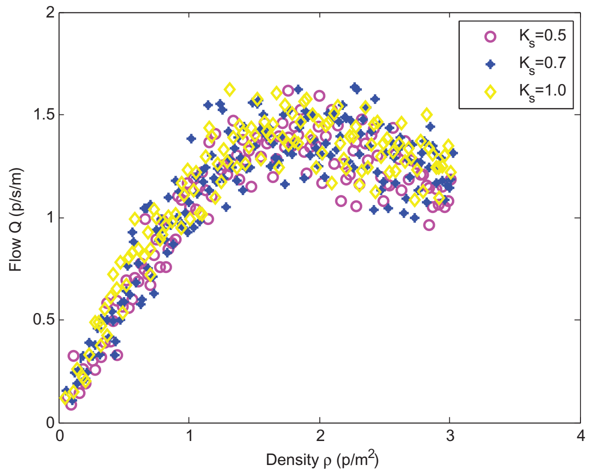

Fig. 15. Comparison of density ρ and specific flow Q for different values of probability K_s.

when the wide of hallway is 8 m. This proves that the result of proposed model is rational in the simulation of bidirectional pedestrian flow in the hallway. Because the time-consuming avoidance behaviors and head-on conflicts are replaced by the simple following behaviors, the passing efficiency of hallway is significantly improved after the lane formation phenomenon is occurred. Simulation results show that the 'lane formation' phenomenon is not a result of the pedestrian organization but an emergent property of the many interactions within bidirectional pedestrian flows.

Then, we investigate the relationship between specific flow and density which is known as another fundamental diagram obeyed by bidirectional pedestrian flows [12,58]. The instantaneous flow in the measurement region is computed as the product of density and average speed. The measurement region of 4 $m \times 8$ m is set in the middle of the hallway. The global density of the hallway is controlled by adjusting the entering flows of both left side and right side, which is varied from one person per second to eight persons per second. The flows of both sides are equal in this simulation. The measurement methods of density and speed are identical with above.

The measured results for the fundamental diagram of density against specific flow (bright blue circles) are shown in Fig. 14. The blue line represents the best fitted curve ($R^2 = 0.907$) obtained by using a least squares procedure. The tendency of the relationship between speed and density is good agreement with that derived by Weidmann [58] and Flötteröd and Lämmel [12] at least for the density $\rho < 3$ p/m^2. The specific flow increases with the enhancing of global density when ρ is relatively small. Global density bigger than 1.8 p/m^2 will not contribute to increasing specific flow.

Meanwhile, we investigate the effect of walking habits on the fundamental diagram of density and specific flow relation. The K_s in (1) depicts probability of a pedestrian selecting the preferred left direction when a pedestrian faces the same preferred right and left conditions, which are both attractive than front sector. The value of $K_s = 0.5$ indicates that a pedestrian's choice is completely random, while $K_s = 1$ indicates the choice is completely decisive. Simulations of bidirectional pedestrian flows are performed in the same hallway scenario with different values of probability K_s. The values of K_s are set as 0.5, 0.7, and 1.0, respectively. Fig. 15 gives the relation of the specific flow Q and crowd densities under different values of probability K_s. We can see that the varying of K_s has negligible influence on the density-specific flow relation at the density domain $\rho < 3\ p/m^2$. This finding is agree with the result of Zhang et al. [66]. One reasonable explanation of this could be that the head-on and cross-directional conflicts occurred in bidirectional pedestrian flow have little impact on the passing efficiency when the density is not too high. That is, the walking habits considered in this study have little effect on the fundamental diagram of bidirectional pedestrian flows at least for density $\rho < 3\ p/m^2$.

In summary, all these simulations show that the proposed fuzzy logic-based model can describes some observed phenomena such as 'arching and clogging', 'faster-is-slower effect' and 'lane formation' realistically, and the measured fundamental diagrams such as speed-time, speed-density, and flow-density relations match well with the empirical results. So we have reason to believe that the proposed model can be applied to a reliable description and prediction of pedestrian dynamic behaviors.

5. Conclusion

The main contribution of this paper is the proposing of a new model for pedestrian dynamical behaviors by using a fuzzy logic approach. First, a pedestrian's visual field is divided into five sectors by radial-based discretization method. The decisions of turning angle and movement speed of each step are made by integration of the intermediate results of local obstacle-avoiding behavior, regional path-searching behavior and global goal-seek behavior with mutable weighting factors. The weighting factors of three elementary behaviors are adjusted automatically with the variation of surrounding environments. By simulations of crowd evacuation, unidirectional and bidirectional pedestrian flows, the effectiveness of the proposed model is validated from both qualitative and quantitative aspects. The self-organization phenomena, such as 'arching and clogging', 'faster-is-slower effect' and 'lane formation', are observed in these simulations. The analyzed results indicate that the tendency of fundamental diagrams are in line with published empirical data. The evacuation time of the proposed model decreases with the increasing of exit width, which is accord with the results of the social force model and CAFE model. Meanwhile, we also found that the walking habits has negligible influence on the fundamental diagram of density-specific flow relation at the density domain $\rho < 3$ p/m^2.

The pedestrian model proposed in this paper embodies the following three human experience or behavioral heuristics:

- A pedestrian keeps a safe distance with the closest obstacle in the walking direction, and turns a suitable angle to avoid collision with it, but he/she dislikes deviating too much from current direction;
- A pedestrian always searches the safest path (the minimum negative energy sector) taking into account the complicated interactions with obstacles and pedestrians in the visual field;
- A pedestrian has the trend of walking toward his/her final goal no matter what the environment.

The proposed fuzzy logic-based pedestrian model has major advantages over exiting analytical methods. First, the model has the ability of making the most of perceptual-based information, which are imprecise and uncertain in nature and often overlooked for other methods during the modeling procedure. This does not, however, mean that the proposed model can't deal with precise information. It has the same processing capability for measurement-based information by treating them as a special form of perceptual-based information. Second, it makes the proposed model highly robust in coping with the cognitive and perceptive disparities of things. And third, the use of human experience and knowledge makes the proposed fuzzy logic model more realistic for description and prediction of pedestrians' behaviors. In addition, the adopted elementary behavioral analysis and weighting integration strategies can be extended conveniently to incorporate new behaviors such as separation and herding behavior, whereas this requires complete reconstruction for analytical methods.

In this paper, pedestrian dynamic behaviors in common scenarios, i.e. a square room with an exit, unidirectional and bidirectional hallways, have been investigated by using the fuzzy logic model. In the subsequent research, the proposed model will be further applied to pedestrian stream simulation in a more complex scenario such as subway station or stadium.

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