ANALYSIS OF PEDESTRIAN DYNAMICAL BEHAVIOUR USING FUZZY LOGIC

Group 13 Term Project

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Introduction

Pedestrian dynamical behaviour refers to the movement strategy a pedestrian use as a part of a large crowd. It is a highly complex phenomenon driven by self-organized processes based on local interactions among pedestrians. It helps in the analysis of crowd evacuation systems, and traffic movement. Such models help in optimizing crowd management using limited traffic resources and helps in planning accidental evacuation strategies. It uses human knowledge and perception about their surroundings, and their general strategy to reach the goal point avoiding nearby collisions. This model can use our fuzzy cognitive abilities in a remarkable way. Such robust model can play crucial role in study of phenomenon like" arching and clogging "for the design of public places .It can also be used for a system of swarm robots.

Problem Definition

Assume a chaotic room filled with n number of individuals, each having random velocity and are present at a random location. All of them just want to get out of the room through a single small door. They don't want to collide with each other or with any other obstacle like wall or table in the room. So, basically we need to model this phenomenon. We will be using general human behaviour and their fuzzy perception about their surroundings. Then from the model we can determine various relations like dependence of time of evacuation on size of door and density of individuals in the room. We can study phenomena like 'arching and clogging', 'faster -is-slower 'effect and 'lane formation'.

Details

To model this problem we use a microscopic model using Fuzzy logic to digest the fuzzy perception and decision making of general human. Using Fuzzy logic we give the model various abilities like *robustly coping with uncertainty and imprecision in our day to day perceived knowledge.* It helps in dealing with uncertainty and vagueness of human cognition. For example while parking a car we don't measure the accurate distance and angle relative to the desired position ,instead we use the term like "slightly left" ,"little right", etc. After defining the physical space, we categorise the strategies of the individual into three sections.

Local obstacle avoiding behaviour

In this strategy the person tries to avoid the local obstacle in its visual span and then accordingly decides the degree of manipulation in velocity vector.

Regional path searching behaviour

In this strategy, the individual tries to look as far as possible and tries to get away from the crowded region .We use the term negative energy for this.

Global goal seeking behaviour

In this strategy the individual tries get closer to the goal point. And then we do weight assignment. The weights are mutable. Finally we run simulations to validate the model. Finally from all this we get the amount of change required in velocity vector .The whole process has been shown in the Figure 2.

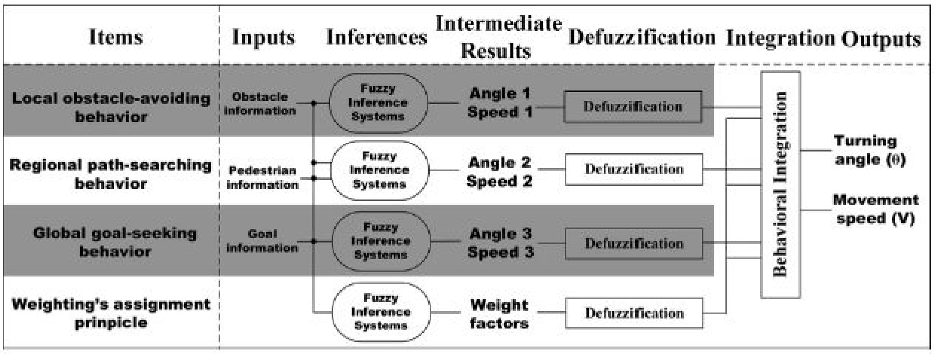


Fig. 2. The overall structure of fuzzy logic based pedestrian model. It mainly consists of five components: inputs, fuzzy inference systems, defuzzification, integration and outputs.

Implementation

We divide the implementation in three basic parts which themselves are further divided.

Defining /representing the space

We use the radial based representation of the space under consideration. An individual is located at its current position p, with the current direction and speed be ϴ and v. And a visual angle of 2 Φ. The goal lies at a distance of d_g and an angle of γ_g .The maximum visual distance be d_{max}. We divide the region in three part local, regional, and global , radially .Now we divide entire region in sectors and name them as shown in figure 1.

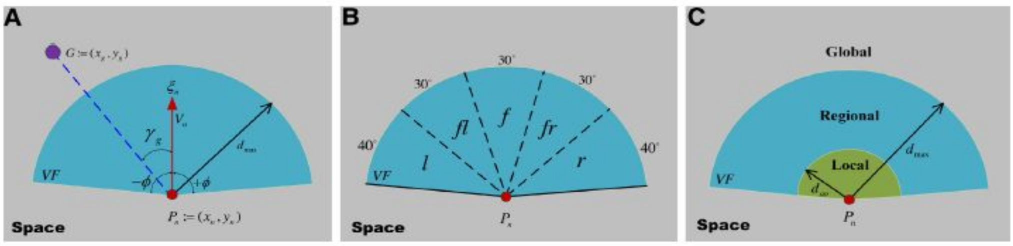


Fig. 1. The sample chart of space representation. (A.) Definition of variables in the descartes rectangular coordinate system: heading direction (ξ_n), movement speed (V_n), goal angle (γ_g), goal distance (d_g), visual angle ($2\phi°$), and horizon distance (d_{max}). (B.) Discretization of space based 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.

We assume that the radius of local region be 3m (it reacts if the obstacle is less than 3m from the individual) and the visual angle be 170 degree and the maximum visual angle (up to where he can see) be 8m .We weight the results from the three strategy according to the live field conditions .If the distance from obstacle is near then the local behaviour is weighted more than the global one . So now the individual look in these 5 sectors at three level (local, regional, and global) and then makes a decision for changing the velocity vector. The change occurs either by changing the angle of movement or magnitude of speed. For that we have a well-defined fuzzy membership for change in speed and change in direction as shown in the figure below. So we apply the strategy and control the velocity vector.

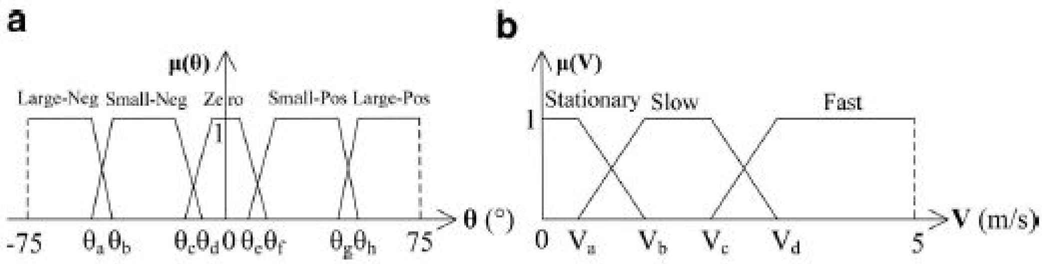


Fig. 3. Membership functions for (a) turning angle, and (b) movement speed.

Basic assumption

We assume that

1. Crowd density is normal
2. Heuristic based walking
3. The individuals don't interact
4. Each individual has a radius of .25 m.
5. The speed follows a Gaussian distribution with mean 1.34m.
6. Individuals have only regional information.

Strategies and their Fuzziness.

We will be using various linguistic term as shown in the figure below

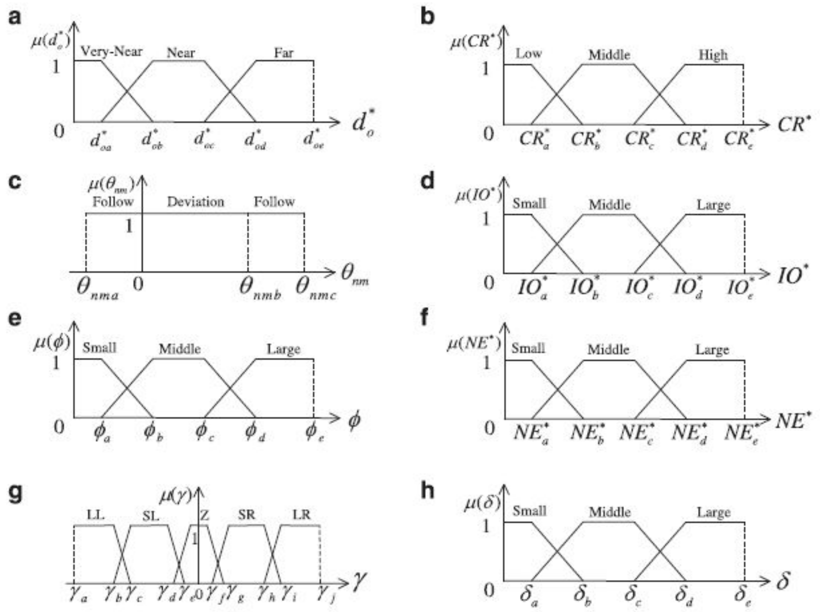


Fig. 4. Membership functions for (a) the closest pedestrian-obstacle distances, (b) collision risk, (c) angles between decision maker and pedestrians, (d) influence of obstacles, (e) angles occupied by obstacles, (f) negative energy, (g) goal angle, and (h) weighting factors.

This decision making process can be divided into 4 steps

Local obstacle avoiding behaviour

To avoid any collision we look for the obstacle in local region. We define distance membership as given in the figure 4. We use two layered fuzzy approach and look for the obstacle in whole right and whole left region along with front region. We use inference rule for the first layer as shown below, where SN refers small negative turn angle similarly for large turn .And N for near and F for far.

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

Here for example in (1,3) LN denotes that if obstacle distance is very near in front left and far in left sector then we need to rotate with large negative angle. Similarly we form inference rule for right sector. The outputs of first layer are denoted by (PR), (PL). The inference rule for second layer is shown below.

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

Here superscript refers to sectors and other liguitic terms are defined in the figure 4.Here z refers to stationary and UNC refers to uncertain .So,in UNC the object will move according to probability assigned for PP(partial positive turn) and PN.Similarly for speed we slow down(obstacle is near),fasten up(if Far) and stop(if Very Near).

Regional path searching behaviour

In this strategy we aim to travel through a region of low NE (negative energy).This NE depends on two factors

Collision Risk

It is a measure of the possibility of collision .It depends on whether the obstacle is approaching or departing away, on the distance of obstacle and its velocity. Its membership function is shown in figure 4.The rules for CR is shown in table below

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

And the expreesion for evaluation is

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

here we sum for all object in the visual range for all the sectors and there sum give us CR . d , v and theta is defined in the figure below.

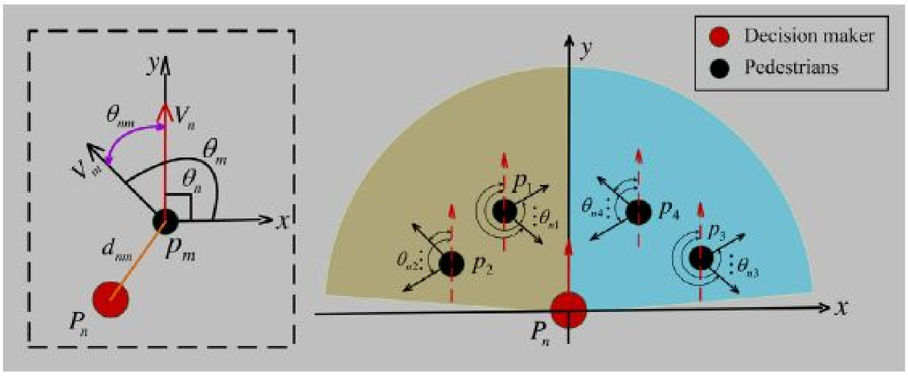


Fig. 5. Illustration of the decision maker P_n facing nearby pedestrians.

Influence of obstacle.

It is a measure of the closest obstacle distance and the angle occupied in the visual range. Its membership function is shown in the figure 4.

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

Where M is the count for all the obstacle in in each sector.

The rules for IO and total NE are as shown in figures.

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

We now calculate NE for each sector and one with minimum NE is selected.

Global goal seeking behaviour: In this strategy we try to move closer to goal. We try to minimize distance from goal in the direction towards goal. We use the following rule

(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.

Integration of behaviour and conflict resolution. Now we may get different results from the three strategies. To solve this problem we use simple weighted mean approach. The weighting scheme we use is dynamic and is controlled by the dynamic surrounding. For example if the local region is obstacle free then we may give less weight to local behaviour and more to global behaviour. So, we finally get speed and angle of turning as

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

equation 3

here the three weight are respectively for local, regional, and global behaviour results. We use counterpart fuzzy set with COG Defuzzification. Finally the weighting assignment rules are shown in the figure.

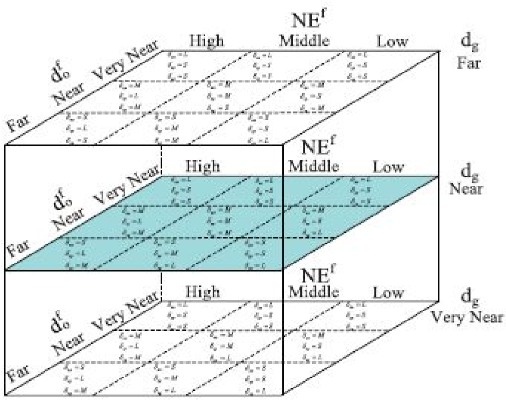


Fig. 7. Weighting's assignment rules for three elementary behaviors.

Results and Discussion

Validation of the model using simulations and controlled experiment was done.
Like an emergency case and the dense crowd pushes forward towards a narrow exit, clogging along with arching was clearly visible. The exit soon became clogged and the crowd formed an arch-shape, radiating outwards from the exit. We saw arching crowd formation and bursting exit strategy. Dependence of evacuation time on desired speed and door width was observed. “Faster is slower “phenomena was also observed. The exit time was proportional of speed and density of crowd and inversely proportional to width of exit. It was possible to decide critical exit width when we had size of room and density of individual. Results are shown in figure below. Bidirectional flow was also examined. In this case increased efficiency was observed due to lane formation. Thus this Fuzzified approach proved its validity by giving it’s result in agreement of other models and empirical values .Various phenomena like “arching and clogging”, ”lane formation”, and “faster-is-slower” was observed. So, we can say that the model has shown its reliability in describing pedestrian dynamics.

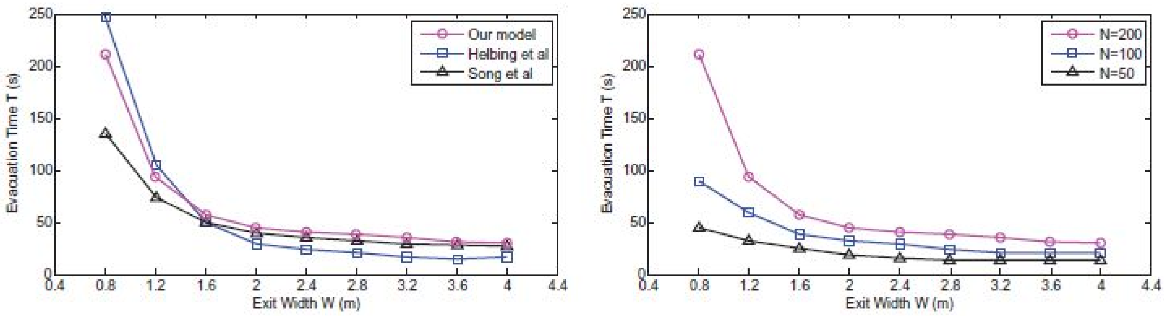
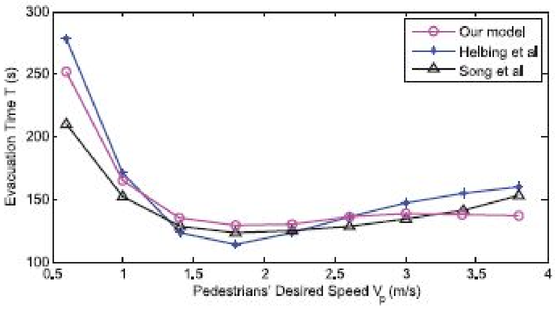


Fig. 10. The influence of exit widths on evacuation times: (a) comparing with empirical results, (b) under different initial densities.



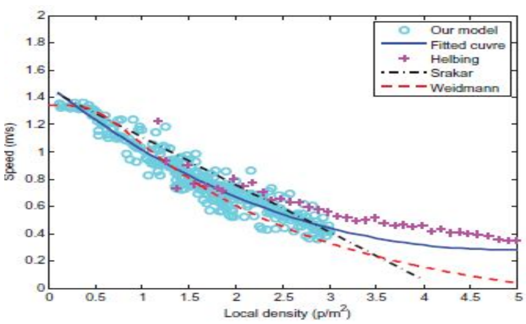


Fig 11.a Fig 11.b

Future Projections

This model can be made more accurate by inserting more characteristics of Human decision making processes. It can be further applied to a large group of people like a crowd in a stadium during a football match. Usually in such cases there are multiple gates and multiple directions .So there are lots of opportunities for the model to grow. The model shows that how we humans coordinate with each other using our perception about our environment and few simple strategies. Such model can be used for the coordination of large group of robots working together. This model shows that how we humans deal with real life problems with *fuzzy information (imprecise and vague).* This remarkable property can be used in the development of *coordinated AI*.