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SIMULATION OF CROWD BEHAVIOR USING FUZZY SOCIAL FORCE MODEL

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ABSTRACT

Social Force Model (SFM) uses mathematical equations to describe pedestrians intentions and interactions. The crowd behavior is a result of these forces acting in each pedestrian. One of the major disadvantages of SFM is the understanding of the pedestrians intentions that are somewhat hidden in the mathematical equations and its parameters. In this paper we propose the implementation of a fuzzy logic based model called Fuzzy Social Force Model, capable to model and simulate crowd behavior. The proposed model translate the forces modeled by SFM equations into desire and interaction effects described by linguistic expression rules and fuzzy sets. This novel model is easier to parameterize, to extend and it presents the same emerging behaviors of the SFM but with a better interpretability. Our approach also offers a natural way to adjust and modify the pedestrians dynamics for panic, low visibility or other specific situations.

1 INTRODUCTION

The ability to model and predict the pedestrian behavior in different situations is essential in a number of situations. In the area of architecture, understand how individuals move into the buildings allows to establish safer environments and better design of circulation areas. In applications as integration of transportation facilities, the simulation of different scenarios can avoid congestion situations and enable quick movement of pedestrians between their destinations. Detection of abnormal pedestrians behavior can be essential in video surveillance systems (Antonini 2005).

Pedestrian behavior can be modeled in many different scales, but it can be broadly divided in two different approaches: macroscopic and microscopic. The object of study the macroscopic models is the crowd itself, while in the microscopic models, pedestrian movement and crowd behavior emerge from the relationship between pedestrians and its surrounding environment. Despite being the more computationally expensive, microscopic models are considered more accurate and powerful than the macroscopic ones. So, in this paper we focus on developing a microscopic model capable to describe pedestrian behavior in scenarios of evacuation simulation.

The three main approaches to the microscopic models are the Cellular Automaton (CA) (Blue, Embrechts, and Adler 1997, Wei-Guo, Yan-Fei, Bing-Hong, and Wei-Cheng 2006, Varas, Cornejo, Mainemer, Toledo, Rogan, Munoz, and Valdivia 2007), Agent Based Methods (ABM) (D"Orazio, Spalazzi, Quagliarini, and Bernardini 2014, Murphy, Brown, and Sreenan 2013, Almeida, Rosseti, and Coelho 2013) and the Social Force Model (SFM) (Helbing, Farkas, and Vicsek 2000, Moussaïd, Helbing, Garnier, Johansson, Combe, and Theraulaz 2009, Helbing and Johansson 2011). The CA approach is a discrete time and spatial model with low computational costs, although it does not accurately represents generic relationships between pedestrians. ABM can be considered the most generic method, and it can accurately describe pedestrians movements. But it can became a slow method, because the movement is modeled with series of rules for each pedestrian, making simulations for large crowds computationally inefficient. SFM is the most reliable and fast microscopic model. In the review made by (Duives, Daamen, and Hoogendoorn 2013), SFM and hybrid models that use SFM shown the best balance between computational cost and accuracy in simulating pedestrian and crowd behaviors.

SFM is based in fluid-dynamic theory concepts and its modeling is done through mathematical equations that describes the physical forces acting on each pedestrian. These forces try to capture different desires or interactions effects, as such: the interactions between pedestrians, the interactions between a pedestrian and the surrounding environment, and the forces that drives the pedestrian intentions. These equations, although simple, are not easily understood and its implementation can be intricate. Additionally, adjustments and changes in order to produce some specific behaviors such as panic, wound pedestrians and others are difficult to perform.

In this paper we propose the implementation of SFM in a fuzzy logic based model called Fuzzy Social Force Model (FSFM) to simulate crowd behavior. The proposed model translates the SFM equations into linguistic expressions rules and fuzzy sets. This novel model is easier to parameterize, extend and it also presents the same emerging behaviors with a better interpretation of the pedestrian behavior that emerges from diverse interactions.

The use of fuzzy logic to model pedestrian behavior is not new, (Nasir, Nahavandi, and Creighton 2012), proposed a hybrid model that uses 216 fuzzy rules implemented on the top of the Social Force Model in order to produce very intricate behaviors. In this paper our intention is to create a minimum set of linguistic rules that brings out the same behavior exhibited by SFM and whose processing time is consistent with the implementations of the SFM.

In the next section we describe the SFM and its equations, briefly review the fundamentals of fuzzy logic and present some related researchs. After that, the proposed Fuzzy Social Force Model is described and the fuzzy rules are presented. In Experiments and Results section we present the experiments that indicate that those behaviors presented by the classical SFM, also appear in the proposed model. Finally we present conclusions and suggestions for future works.

2 RELATED WORK

In this section we present a detailed description of the forces and equations that compound the Social Force Model. Some emerging behaviors, typical of crowd evacuation scenarios, are mentioned and a brief description of Fuzzy Logic fundamentals is presented.

2.1 Social Force Model

The Social Force Model (SFM) was proposed by (Helbing and Molnar 1995). SFM is based on interaction forces, which characterize the pedestrian's psychological intentions to move. When an imbalance occurs between the intentions of the pedestrian and its present situation, forces increase in order to take it into a new equilibrium point. SFM treats pedestrians as particles (circles) with mass. These ”particles” are attracted towards a local objective (waypoints) while being repelled from other ”particles” and obstacles at the same time. Since it was proposed, SFM equations were improved and modified. In this paper we describe those equations presented in (Helbing, Farkas, and Vicsek 2000, Moussaïd, Helbing, Garnier, Johansson, Combe, and Theraulaz 2009, Helbing and Johansson 2011).

The SFM is composed by four forces and its general equation is given in Equation 1.

$$m_i \frac{dv_i}{dt} = desired_i + \sum_{j \neq i} social_{ij} + obstacle_{iw} + \varepsilon \qquad (1)$$

where $m_i \frac{dv_i}{dt}$ is the resultant force applied to a given agent and $desired_i$ is called the Desired Force, $\sum_{j \neq i} social_{ij}$ is the Social Force and $obstacle_{iw}$ is the Obstacle Force while ε is a random term. In the following subsections each of the components of Equation 1 are detailed.

Both the Obstacle and the Social Force are compound by a term called Granular Force $gran_i$, this term is the physical force when the pedestrian bumps into another pedestrian or obstacle. The term $gran_i$ won't be explained in this paper because we haven't altered him because he reflects a physical force, not a psychological one, as such, he does not need to be simplified or translated to linguistic fuzzy rules.

2.1.1 Desired Force

Desired Force (Equation 2) is the force that attracts the pedestrian to an objective.

$$desired_i = \frac{v_i^0 \overrightarrow{e_i^0} - \overrightarrow{v_i}}{\tau_i} \tag{2}$$

where velocity v_i^0 is the velocity that the pedestrian i wants to achieve, $\overrightarrow{e_i^0}$ is the normalized vector pointing to the direction where the pedestrian (i) wants to go (see Equation **??**), $\overrightarrow{v_i}$ is the pedestrian current velocity and τ_i is the time relaxing constant.

2.1.2 Obstacle Force

Obstacle Force (Equation 3) is the force that repels the pedestrian from obstacles. It depends only on the distance and exponentially decays with the distance to the nearest obstacle.

$$obstacle_{iw}(\overrightarrow{x_i}, \overrightarrow{x_w}, r_i) = [A_i exp(\frac{r_i - d_{iw}}{B_{iw}})]\overrightarrow{e_{iw}} + gran_i() \tag{3}$$

where $\overrightarrow{x_i}$ is the pedestrian position, $\overrightarrow{x_w}$ is the nearest obstacle position and r_i is the pedestrian radius.

Where constant A_i and B_i are constants. $d_{ij} = ||\overrightarrow{x_w} - \overrightarrow{x_i}||$ is the distance between the nearest obstacle point $\overrightarrow{x_w}$ and pedestrian position.

The repulsive direction vector $\overrightarrow{e_{iw}}$ is a normalized vector pointing from the nearest point $\overrightarrow{x_w}$ in the obstacle to the pedestrian i.

2.1.3 Social Force

Social force is the force that repels the pedestrian from other pedestrians, avoiding collisions. It is described in Equation 4.

$$social_{ij}(\overrightarrow{x_i}, \overrightarrow{x_j}, \overrightarrow{v_{ij}}, r_{ij}) = gran_i() + r_{ij}(\overrightarrow{x_i}, \overrightarrow{x_j}, \overrightarrow{v_{ij}}, r_{ij}) + t_{ij}(\overrightarrow{x_i}, \overrightarrow{x_j}, \overrightarrow{v_{ij}}, r_{ij}) \tag{4}$$

The term $r_{ij}(\overrightarrow{x_i}, \overrightarrow{x_j}, \overrightarrow{v_{ij}}, r_{ij})$ is presented in Equation 5 and represents the force that models the intention to slow down to avoid contact with another pedestrian. It's the repulsive part in the social force, where $\overrightarrow{x_i}$ is the pedestrian i's position, $\overrightarrow{x_j}$ is the pedestrian j's position and $\overrightarrow{v_{ij}}$ is the relative velocity between pedestrians i and j while r_{ij} is the sum of the pedestrians radius.

$$r_{ij}(\overrightarrow{x_i}, \overrightarrow{x_j}, \overrightarrow{v_{ij}}) = -A_i \ exp(\frac{(r_{ij} - d_{ij})}{B_{ij}} - (nB_{ij}\theta)^2)\overrightarrow{t_{ij}} \tag{5}$$

where the $-A_i \ exp(\frac{(r_{ij} - d_{ij})}{B_{ij}} - (nB_{ij}\theta)^2)$ term calculates the intention's strength and the vector $\overrightarrow{t_{ij}}$ gives the direction of the movement. Constant A_i is the individual interaction strength (the larger it is, stronger will be the intention).

Variable B_{ij} is the interaction range, in the first SFM's version it was a constant with subsequent research as in (Moussaïd, Helbing, Garnier, Johansson, Combe, and Theraulaz 2009), it was discovered that it has to be a dependent on the velocity and angle of movement as described in the following equation $B_{ij} = \gamma||\overrightarrow{T_{ij}}||$.

Where constant γ is the interaction vector force and the vector $\overrightarrow{T_{ij}}$ is the interaction vector. The interaction vector formula is $\overrightarrow{T_{ij}} = \lambda\overrightarrow{v_{ij}} + \overrightarrow{e_{ij}}$.

Where λ is a constant.

The constant n is the angular interaction range.

The variable θ is the lowest angle between the relative velocity vector and the interaction vector. It's value goes from $-\pi$ (totally left) and π (totally right).

The vector $\overrightarrow{t_{ij}}$ is the normalized interaction vector that points to the direction where pedestrian's i slows down. It's equation is $\overrightarrow{t_{ij}} = \frac{\overrightarrow{T_{ij}}}{||\overrightarrow{T_{ij}}||}$

The turning term $t_{ij}(\overrightarrow{x_i}, \overrightarrow{x_j}, \overrightarrow{v_{ij}})$ is responsible by making the pedestrian change its direction when it moves towards another pedestrian.

The term t_{ij} described in Equation 6 is very similar to the repulsive function, the only differences are the left/right signal K_θ, the different n' angular interaction range and the direction vector $\overrightarrow{n_{ij}}$.

$$t_{ij}(\overrightarrow{x_i}, \overrightarrow{x_j}, \overrightarrow{v_{ij}}) = -A_i K_\theta \; exp(\frac{(r_{ij} - d_{ij})}{B_{ij}} - (n' B_{ij} \theta)^2)\overrightarrow{n_{ij}} \tag{6}$$

The left/right signal K_θ indicates which directions the pedestrian should go, -1 (left) and (1) right. It's equation is $K_\theta = \frac{\theta}{|\theta|}$

Constant n' has the same objective as the n constant, to be the angular interaction range, the greater the n', the faster the angle will change the force, but n' will always be big, because experiments show that pedestrians in general have a tendency to change the direction when they see another pedestrian.(Moussaïd, Helbing, Garnier, Johansson, Combe, and Theraulaz 2009)

Finally the direction vector $\overrightarrow{n_{ij}}$ is a vector perpendicular to vector $\overrightarrow{t_{ij}}$ pointing to the left. The simplest way to calculate is $\overrightarrow{n_{ij}} = [-t_{ij2}, t_{ij1}]$.

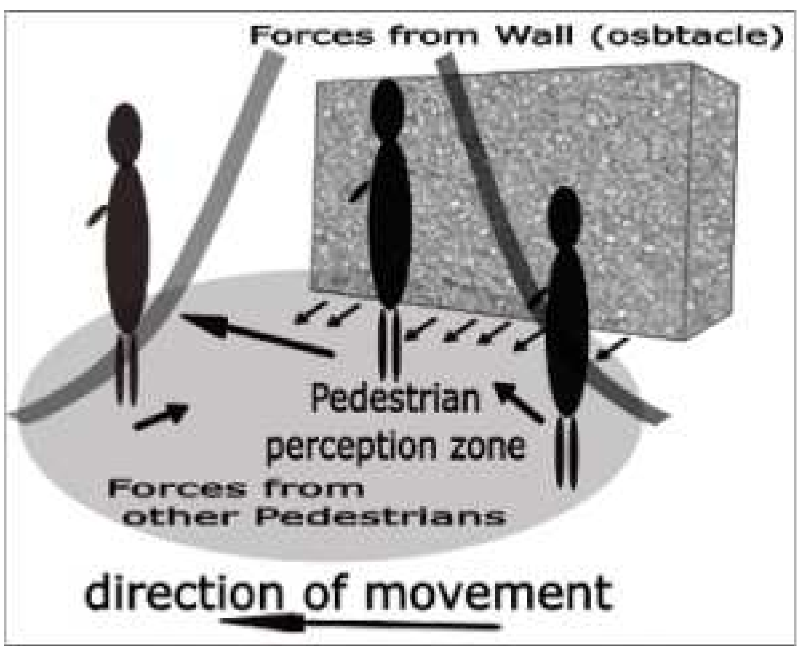

Figure 1: Graphical representation of the SFM.

Figure 1 shows schematically the forces that act over a pedestrian while he moves towards a desired place in the environment. At a given moment, the pedestrian intend to go towards a desired direction, but,if he goes straight in that direction, he will collide with another pedestrian. So he must change his course and decelerate to avoid the collision with other pedestrian. At the same time he realize that he is too close to a wall and feels himself repelled by that obstacle. From these psychological intentions and interactions with other pedestrians and obstacles in the environment, the SFM brings out the apparent behavior of the crowd.

2.1.4 Emerging Pedestrian Behaviors

The reason that SFM is so popular is because it can reproduce well known phenomena of crowd behaviors. Above are listed some phenomena that SFM can reproduce and that we intend that can also be reproduced by FSFM:

Avoidance The pedestrian should avoid contact with other pedestrians and obstacles before it collides.

Faster is slower The faster the pedestrians try to move, the crowded become the exit areas, which slow downs the pedestrian flow.

Lane formation In crowded corridors the pedestrians try to move in lanes. The same thing happens if there are two crowds moving in opposite directions.

2.2 Fuzzy Logic

Fuzzy logic is a form of many-valued logic that was proposed by (Zadeh 1965). It uses degrees of truth to describe the vagueness in propositions. Fuzzy system uses linguistic rules in the form "$IF\ variable_{input}\ IS\ fuzzy\_set\ THEN\ variable_{output}\ IS\ fuzzy\_set$" to describe the relationship between the input variables and the output ones.

Fuzzy Inference Systems process the fuzzy logic expressed in the fuzzy rules in three steps:

1. Fuzzification, which transforms crisp variables values into fuzzy variables.
2. Inference, which uses the fuzzy rules to calculate the values of the sets that make the fuzzy output variable from the fuzzy input variables.
3. Defuzzification, that transform the fuzzy output variables in a crisp output value.

Each fuzzy variable has some fuzzy sets to describe the degrees of truth. Each set is represented by a function. The value in the x coordinate at this function represents the crisp value and the value in the y coordinate, is between 1 and 0 and represents the degree of truth. The rules express explicitly the knowledge and makes easy to understand, parametrize and extend.

Due to his natural and buit-in way, fuzzy inference systems are used in many fields to provide a simple and computationally efficient way to deal with a wide range of problems. Fuzzy is so pervarsive that according to (Dubois and Prade 1997) the membership function can be interpreted in three different semantic ways: similarity, preference and uncertainty. Similarity means how much alike is a piece of information in relation to a respective fuzzy set, it's used in fuzzy cluster set analysis and related systems. Preference is how much feasible is a choice, it's mostly used in engineering. Uncertainty, is the vagueness, the degree of possibility, this view has been used in expert systems, and artificial intelligence. These interpretations are not mutually exclusive, but help to demonstrate the objective in a fuzzy inference system. This model follows mostly a preference interpretation, but we also could interpret as treating the inherited subjective uncertainty in pedestrian behavior.

(Nasir, Nahavandi, and Creighton 2012) proposed an agent based method that uses fuzzy rules to model the pedestrian behavior. They found out that estimating fuzzy rules parameters from real data is an easier task and produces more accurate results. This approach works well, (Nasir, Nahavandi, and Creighton 2012) designed fuzzy rules on top of the SFM, using SFM output as input to the fuzzy system, and it amounted to 216 rules.

More importantly, deriving linguistic fuzzy rules makes the model easier to understand, therefore, requiring less effort to fine tune. Moreover, it has potential to be more accurate than SFM when trained with real data using machine learning techniques, as has been presented in (Nasir, Lim, Nahavandi, and Creighton 2014).

3 PROPOSED MODEL

During research and experiments related to modeling the dynamic behavior of pedestrians using fuzzy logic, several ideas were tested and evaluated. Instead of trying to describe all the interactions between the components of the model without a basic guide, we decided to use the interactions between components already developed for the SFM. In doing so, we believe that our model would be more readable and understandable by users, and at the same time, could be easily adapted and extended to a model of new types of human behavior. In addition, the maintenance of computational performance presented by SFM is an important goal we seek to achieve.

The proposed model inherits all the advantages and the shortcomings of SFM. SFM consider all the pedestrians as independent and all feel repulsive forces towards one another. This is not true in various real situations, for example people in a dancing floor and families or group of friends where pedestrians try to act as small groups. While FSFM still has these incapacities, we believe that by using linguistic rules, it would be easier to create new rules to reflect attraction towards family and friends than create mathematical equations that reflect this behavior. The linguistic rules also would represent the knowledge directly. In order to achieve this objective and show the applicability of our ideas, we manage to translate all social force model in a series of fuzzy rules, and each represents part of one or one of the three main forces, the social force, the obstacle force and the desired force. The sum of these three force makes the SFM. The social force cannot be confused with the SFM, as the first is the main force that composes the later. The social force is divided in three small fuzzy systems (angle, intensity and deceleration), the desired is divided in two (angle, intensity), and the obstacle force is composed by just one (force intensity). The obstacle angle is always perpendicular to the obstacle.

In our fuzzy inference system we use the algebraic product as t-norm as it gives a smother output to the rules.

All the parameters used have been empirically adjusted.

In conformity with previous SFM works we used the metric system.

This work used three types of membership functions, Sigmoid, Gaussian Triangular, presented in Equations 7,8 and 9 respectively.

$$sigmf(x) = 1.0/(1.0 + e^{-slope*(x-inflection)}) \tag{7}$$

$$gaussmf(x) = e^{-((x-c)^2/2s^2)}) \tag{8}$$

$$triangmf(d_r) = \begin{cases} 0 & \text{if } (x < a)||(x > c) \\ 1 & \text{if } x == b \\ (x-a)/(b-a) & \text{if } x < b \\ (c-x)/(c-b) & \text{otherwise} \end{cases} \tag{9}$$

3.1 Fuzzy Desired Force

In order to feel comfortable, the pedestrian aims to be in a desired direction and speed. In an evacuation scenario the direction is the exit door and the speed is the maximum velocity that the pedestrian can or wants to achieve. So, we separate each of these intentions in its own subset of rules, one to treat the direction (angle) and other to treat the intensity.

```
if DirectionAngle is BACKLEFT then AngleTurn is STRONGRIGHT
if DirectionAngle is FRONTLEFT then AngleTurn is WEAKRIGHT
if DirectionAngle is FRONT then AngleTurn is CENTER
```

```
if DirectionAngle is FRONTRIGHT then AngleTurn is WEAKLEFT
if DirectionAngle is BACKRIGHT then AngleTurn is STRONGLEFT
```

The input variable *DirectionAngle* is split in five gaussian sets each one representing a range of the angle where negatives values are left angles in relation to the desired angle. The sets configurations is: The BACKLEFT set is $c = -\pi$ and $s = 0.2\pi$, FRONTLEFT set is $c = -0.5\pi$ and $s = 0.2\pi$, FRONT set is $c = 0$ and $s = 0.2\pi$, FRONTRIGHT set is $c = 0.5\pi$ and $s = 0.2\pi$, BACKRIGHT set is $c = \pi$ and $s = 0.2\pi$.

The output variable *AngleTurn* is split in five triangular sets, each one representing a range of the angle where negatives values are left angles and positive are right angles in relation to the actual velocity. The sets configuration: STRONGLEFT set is $a = -1.5\pi$ and $c = -0.5\pi$, WEAKLEFT set is $a = -\pi$ and $c = 0$, CENTER set is $a = -0.5\pi$ and $c = 0.5\pi$, WEAKRIGHT set is $a = 0$ and $c = \pi$, STRONGRIGHT set is $a = 0.5\pi$ and $c = 1.5\pi$. Where $b = (a+c)/2$ for all sets.

```
if VelocityDifference is VERYSLOW then Force is STRONGPOSITIVE
if VelocityDifference is SLOW then Force is POSITIVE
if VelocityDifference is FINE then Force is ZERO
if VelocityDifference is FAST then Force is NEGATIVE
if VelocityDifference is VERYFAST then Force is STRONGNEGATIVE
```

The input variable $VelocityDifference$ is split in five gaussian sets each one representing a range of speed which is the percentual of speed in relation with the desired speed(v_i^0). So the equation is $VelocityDifference = \vec{v_i}/v_i^0 - 1$. The sets configurations is: The VERYSLOW set is $c = -2$ and $s = 0.4$, SLOW set is $c = -1$ and $s = 0.4$, FINE set is $c = 0$ and $s = 0.4$, FAST set is $c = 1$ and $s = 0.4$, VERYFAST set is $c = 2$ and $s = 0.4$.

The output variable *Force* is split in five triangular sets, each one representing the change of velocity in relation to the actual velocity. The sets configuration: STRONGNEGATIVE set is $a = -3$ and $c = -1$, NEGATIVE set is $a = -2$ and $c = 0$, ZERO set is $a = -1$ and $c = 1$, POSITIVE set is $a = 0$ and $c = 1$, STRONGPOSITIVE set is $a = 1$ and $c = 3$. Where $b = (a+c)/2$ for all sets.

3.2 Fuzzy Obstacle Force

The Obstacle Force function has distance as input argument and provides the force vector as output. The vector direction isn't calculated with fuzzy, as it is simply a vector perpendicular to the obstacle. The force strength is calculated with two fuzzy rules:

```
if DISTANCE is NEAR then FORCE is HIGH
if DISTANCE is FAR then FORCE is LOW
```

We used sigmoidal membership functions to the DISTANCE's sets NEAR and FAR and triangular to the forces values HIGH and LOW. The parameters to the sigmoidal are parameters $slope = -75.0$, $inflection = 0.1$ to the NEAR set and $slope = 25.0$, $inflection = 0.3$ to the FAR set.

The force output was divided in two sets with triangular membership. The parameters are $a = -3$, $b = 0$ and $c = 3$ to the LOW set and $a = 2.99$, $b = 3$ and $c = 3.01$ to theHIGH set. The force is measured in m/s^2.

3.3 Fuzzy Social Force

The social force takes the distance, velocity and angle as input and provides the force vector as output. We separate in three fuzzy series of fuzzy rules to treat the social interaction. The final output in our model is also a force, but each part is treated separately. The strength is the discomfort that the pedestrian is feeling, the angle is the base direction it wans to take to avoid contact and the deceleration is the amount of velocity that the pedestrian aims to reduce. The angle is transformed in a directional vector with *cos* and *sin* that is multiplied by the strength and summed with the deceleration. The force strength is calculated with only four fuzzy rules:

```
if Distance is FAR then Force is LOW
if Velocity is SLOW then Force is LOW
if Angle is BIG then Force is LOW
if Distance is FAR AND Velocity is FAST and ANGLE is SMALL
then Force is HIGH
```

The Distance variable was divided in two terms FAR and NEAR (Figure 2). The type of membership function used is a sigmoid with parameters $slope = 1$, $inflection = 2.5$ to the FAR set and $slope = -1.8$, $inflection = 2.5$ to the NEAR. The Distance is measured in meters.

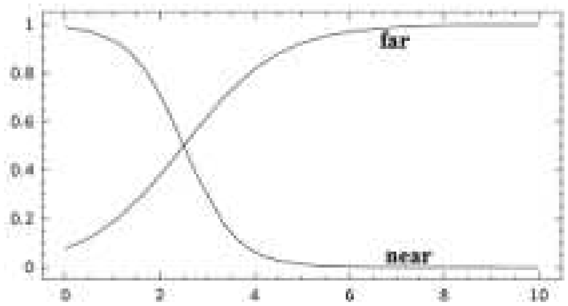

Figure 2: Near and far membership functions accordingly with the distance in meters.

The Velocity variable has been divided in SLOW and FAST sets. The type of membership function is also a sigmoid with parameters $slope = 1$, $inflection = 2.4$ to the FAST set and $slope = -6.0$, $inflection = 1.7$ to the SLOW set. The Velocity is measured in meters per second.

The Angle variable was divided in BIG and SMALL sets (Figure 3). The type of membership function is gaussian with parameters $c = 0$, $s = 0.25\pi$ to the SMALL set and $s = 0.35\pi$, $c = \pi$ to the BIG set. The Angle is measured in radians.

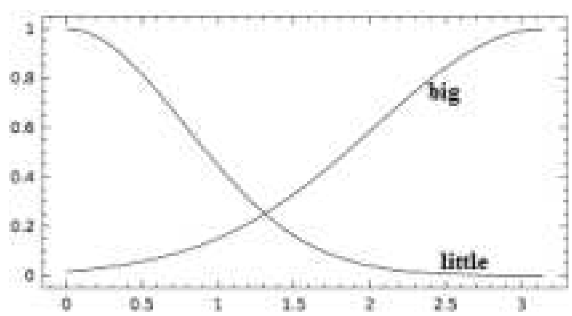

Figure 3: Small and big membership functions accordingly with the angle in radians.

The output variable Force was divided in HIGH and LOW. The type of membership function is triangular with parameters $A = -0.8$, $B = 0.0$ and $C = 0.8$ to the LOW set and $A = 0.6$, $B = 0.8$ and $C = 1.0$ to the HIGH set. The Force is measured in m/s^2.

The angle of the interaction vector($atan2(i.y, i.x)$) is always between the relative velocity vector($\overrightarrow{v_{ij}}$) and the angle of the vector pointing from pedestrian i to j $\overrightarrow{e_{ij}}$. As the relative velocity increases, the interaction's angle goes from the angle between the pedestrians, to the relative velocity angle. In conformity with this, we build a small fuzzy system that the output are from 0 to 1. We simply multiply this output by the difference between the angles in the vector $\overrightarrow{v_{ij}}$ and $\overrightarrow{e_{ij}}$ and sum with the angle of the vector $\overrightarrow{e_{ij}}$. The rules are:

```
if RelativeVelocity is ZERO then TurnPercentil is ZERO
if RelativeVelocity is WEAK then TurnPercentil is WEAK
if RelativeVelocity is STRONG then TurnPercentil is STRONG
```

The RelativeVelocity variable was divided in ZERO, WEAK and STRONG. The type of membership function is gaussian with parameters $c = 0$, $s = 0.4$ to the ZERO set,$c = 1$, $s = 0.4$ to the WEAK set and $c = 2$, $s = 0.4$ to the STRONG set. The relative velocity is measured in meters per second.

The TurnPercentil was also divided in three sets, ZERO and WEAK and STRONG. The type of membership function is triangular with parameters $a = -0.5$, $b = 0.0$ and $c = 0.5$ to the ZERO set,$a = 0.0$, $b = 0.5$ and $c = 1.0$ to the WEAK and $a = 0.5$, $b = 1.0$ and $c = 1.5$ to the STRONG.

The need to treat the pedestrian deceleration in separate fuzzy rules is because the pedestrian shows a tendency to change direction and avoid decelerate. This was observed by (Moussaïd, Helbing, Garnier, Johansson, Combe, and Theraulaz 2009) and for that reason $n < n'$ in his modeling of social force model. The input in this fuzzy rule is the output of the first four fuzzy rules, or the final strength. As the strength (pedestrian discomfort) increases. The tendency to slow down decrease. The output is the percentage related to the strength itself that deceleration gets. To Accomplish that we use only three fuzzy rules:

```
if Force is ZERO then Deceleration is STRONG
if Force is WEAK then Deceleration is WEAK
if Force is STRONG then Deceleration is ZERO
```

The Force was divided in ZERO and WEAK and STRONG. The type of membership function is Gaussian with parameters $c = 0$, $s = 0.133$ to the ZERO set,$c = 0.3$, $s = 0.133$ to the WEAK and $c = 0.6$, $s = 0.13$ to the STRONG. The Force is measured in meters per second.

The Deceleration was also divided in three sets, ZERO and WEAK and STRONG. The type of membership function is triangular with parameters $a = -0.5$, $b = 0.0$ and $c = 0.5$ to the ZERO set,$a = 0.0$, $b = 0.5$ and $c = 1.0$ to the WEAK and $a = 0.5$, $b = 1.0$ and $c = 1.5$ to the STRONG.

4 EXPERIMENTS AND RESULTS

In order to reduce the computational burden, we develop our own fuzzy library optimized. Using Julia Language meta-programming capabilities to generate one function per fuzzy system that processes all three steps of a fuzzy system (fuzzification, inference and defuzzification) in one single function call avoiding unnecessary function calls. All the variables that are parameters or just calculated from parameters in the fuzzy system have been made constants inside the function. The defuzzification calculates directly the centroid without integrate, thus avoiding a loop that would require a lot more processors cycles. In doing so, we can make the FSFM almost as fast as the normal SFM with the increase time between 10% and 50%.

In order to validate our model in its ability to reproduce pedestrian behavior phenomena and its computational performance, when comparing with SFM. We tested the FSFM in two scenarios, one is the simulation of an escape route with a wider area as show in Figure 4 (a). The other is a simulation with 640 pedestrians evacuating a building floor. The floor has 16 rooms, each with 40 people, as can be seen in Figure 4 (b). The (a) shows the pedestrians scattering when they come from a very narrow corridor and enter in a open space, when the pedestrians try to enter again in the narrow corridor, they form lanes in both sides.

When the simulation is run, we can easily observe the ”lane formation” and the ”faster is slower effects”. The pedestrians also slows down/stop in order to avoid collision with other pedestrians. The pedestrians are all waiting by the door. This happens only when the desired force is working correctly and balanced with the social. As shown in Figure 5.

We can see that when pedestrians try to evacuate a set of rooms along a hallway, those rooms located at the end of the hall are the first to be emptied, while the rooms that are close to the hallway output are the last to be emptied because the occupants of these rooms can not enter the hall due to the large amount

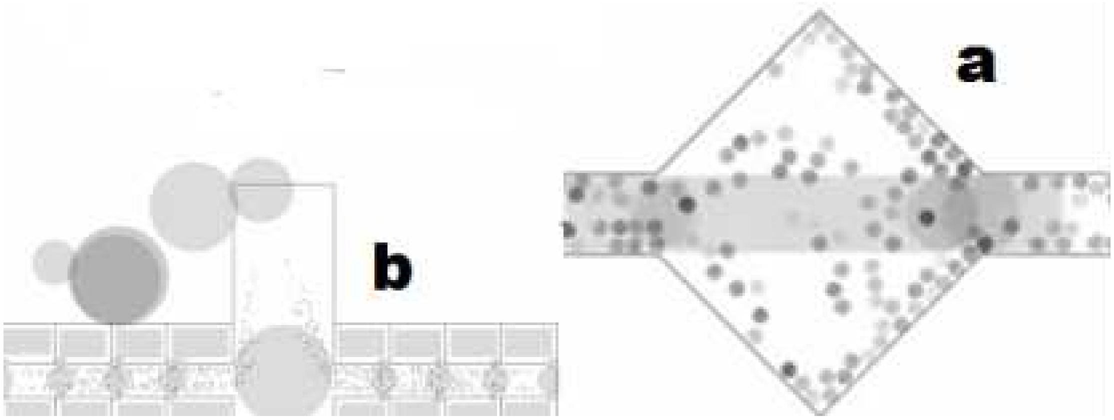

Figure 4: Lane formation

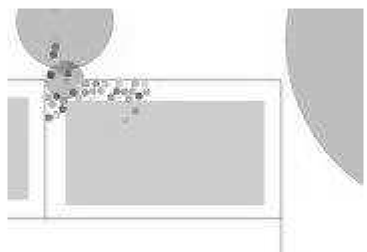

Figure 5: Pedestrians waiting around the door

of pedestrians who are walking through the hallway. As shown by Figure 6. Where we present the first moments in the simulations above the last ones. At the first moments all the rooms are full, in the last, just the rooms located at the end of the all.

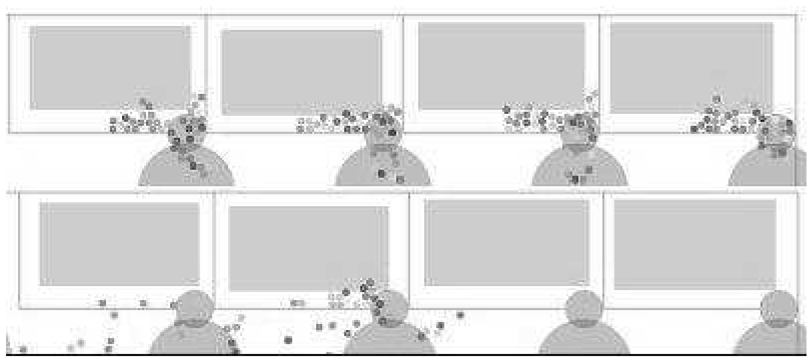

Figure 6: Middle rooms are the last to evacuate.

We also can note that the when the pedestrians change abruptly the direction, they start to bump one in another. This effect also happens in very crowded areas. This effect can be seen in the Figure 7. We drawn lines to show the approximate direction of movement in each place.

5 CONCLUSION

The preliminary results show that this model can replace the SFM with fuzzy rules modeling the pedestrian behavior. This model consists of only 22 rules for the core part of SFM and shares the same capabilities

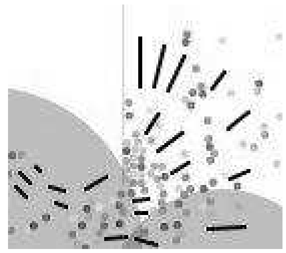

Figure 7: Abrupt change in direction.

and shortcomings presented on the SFM. It's clear that using fuzzy linguistic rules removes the unnecessary complexity of the SFM without increasing heavily the computational cost. We understood as complex the gap between the knowledge and the way that this knowledge is expressed. Mathematical equations in the SFM are more complex than it needs to be to express a very simple idea. The simplicity in the SFM is somewhat hidden by the mathematical equations. Our model uses fuzzy linguistic rules. Fuzzy rules shortens the gap between SFM's modeled knowledge and human language thus reducing the complexity. This way, we think that it would be easier to improve the FSFM model and extend to model types of problems which were previously impossible with the SFM.

In this work the membership functions of fuzzy sets were calibrated empirically. First we plotted the force and tried to understand each parameter in the equation to develop the fuzzy rules. Second, we plotted the fuzzy rules and tried to adjust the fuzzy sets to look closer to the original force, when we failed in the process, we went back to the first step and tried to understand which aspect we still haven't understood. In the third step we replaced the original force, by the fuzzy force in the original model, ran a simulation and evaluate the simulation, just looking and seeing if it continue to reproduce the behaviors presented in the original model. We did this three steps till replace all the forces in the original model. When we finished, we had a model with similar capabilities, but using fuzzy rules instead of mathematical equations. This approach in our vision is incomplete. We believe that applying machine learning techniques using real evacuation scenarios as training set could improve the results.

We published the source code in (Altieres 2014), so other researchers can test and extend FSFM.

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