**EXPLORING THE HETEROGENEITY** **INSIDE POPULATION**

**TO ENHANCE CROWD MODELLING OF GROUP DYNAMICS**

1. **Introduction**

Rapid urbanization and population growth are always inevitable challenges for every country in the effort of planning infrastructure, estimating traffic needs and capacities, and increasing the safety of pedestrians since over 70% of the world population is predicted to live in cities by 2050 (Weidmann, 2012). With the increase in the number of public events and the number of accidents during these events (Evers, 2011), the demand for realistic crowd simulation models becomes important for risk management in urban design and crowd safety. To develop realistic simulation models, various studies have been conducted in understanding and simulating behaviours which can unfold in both normal and emergency situations such as groups of pedestrians moving with or compete against each other.

Group cohesion behaviour is the behaviour of objects moving towards the average positions of their neighbours over the time (Reynolds, 1987). The definition of this behaviour was motivated by the visual appearance of coherently flying objects. The behaviour has been then investigated widely on the collective motion of different flocking organisms including homing pigeon flocks (Kattas, 2012) (Nagy & Vicsek, 2010), fish schools (Miller & Couzin, 2013), and bacteria colony (Cisneros, 2007).

Human group cohesion behaviour is observed by its cohesion degree and formation. Cohesion degree denotes the average distance to the group’s centre of mass from each group member while observable human group formations are V-like, line-abreast, U-like, or river-like (Helbing, 2005). Group cohesion behaviour is important in both normal and evacuation scenarios. In normal situations, group cohesion behaviour can affect the speed and movement direction of pedestrians who are not belonging to any group. In human behaviour research, group cohesion behaviour has been observed in the UK at different places of train station, shopping centre, university campus, Clumber Street with the percentages of 37 %, 50%, 28%, 50%, respectively (Singh, 2009). Pedestrians in the same group might be family members, colleagues. In crowd disasters, pedestrians evacuate with group rather than escape individually. Groups of families and friends with strong ties, stay together and evacuate together have been emphasized through socio-psychological research area (Mawson, 2005). They may move irrationally to maintain its cohesion and consequently become obstacles for other pedestrians (Aguirre, 2011).

Various models have been proposed to simulate group cohesion behaviour such as the social-force based model, the cellular automata model, the standard Vicsek model. These models mainly investigate how group’s formation, cohesion degree, and speed change when group population size varies, and explore the collective behaviour of flocking organisms when varying model’s parameters. Group members are considered as homogeneous through using the same parameter distribution. It is caused by the fact that these model’s authors consider group members as particles. Thus, they have not yet explored the impact of the difference in between group member’s parameter distributions, even though an actual group contains different group members, whose individual physical parameters (speed, interaction range and strength) are different to those of others. Groups of different members can be easily seen in both of normal and emergency situations. In emergency situations, a study (Aguirre, 2011) found that a pedestrian may select another pedestrian based on demographic traits to move together in a group through the crush disaster that happened at the Nightclub, USA in 2003.

Therefore, this PhD study aims to investigate the effect of setting different parameter distributions for group members on the group cohesion behaviour models. This impact is investigated on flow rate and group cohesion degree through proposed case studies of simulation scenarios.

Section 2 of this report represents the state of the art from models of group cohesion behaviour and their advantages and limitations. Section 3 analyses the drawbacks of current models and presents the need for this research study. Section 4 presents proposed research questions. Section 5 presents research methodology to resolve these questions. Section 6 reports the contribution and challenge of this study. Section 7 reports current work in progress for answering these questions. Finally, section 8 outlines compulsory research training hours undertaken in the IT faculty.

1. **Literature Review**

This section reviews current models that incorporate group behaviour. Modelling approaches are various from investigating social forces that affect each pedestrian’s acceleration, modelling the changes of each cell on a grid layout, to providing standard Vicsek model which has been applied widely in flocking organisms.

**2.1. Social force model for group behaviour**

Moussaid, Helbing and colleagues (Moussaid, 2010) created the social group model based on the social-force model (Helbing & Molnar, 1995, 2000). The social group model (equation 1-2) represents that a pedestrian *p* at time *t* is trying to move with a certain desired speed in a desired direction pointing from pedestrian *p*’s current position to his target position. Therefore, pedestrian *p* tends to correspondingly adapt his actual velocity with a certain acceleration time . The acceleration time represents pedestrian *p* changes its current velocity and return to its desired velocity. Pedestrian *p*’s acceleration at time *t* is also influenced by repulsive forces coming from surrounding pedestrians and obstacles. They are and respectively. The repulsive force’s directions and group force direction are represented in Figure 1. The group influence force aims to describe that an individual in group continuously adjusts its position to reduce its head direction and maintain group’s centre of mass, but also avoid other group members. The group force is represented in equation 3.

|  |  |
| --- | --- |
|  | (1) |
| = | (2) |
|  |  |

where is the desired speed of pedestrian *p* that varies over time, is an uncertainty factor.

|  |  |
| --- | --- |
|  | (3) |



**Fig 1**. Repulsive forces and on pedestrian *p* created by pedestrian *q* and wall γ.

The social group force describes that pedestrian p at time *t* turns his gazing direction to see their partners. Thus, vision force is included to help pedestrian p adjust its position to reduce the head rotation. At the same time, pedestrian p keeps a certain distance to the group’s centre of mass by the force . A repulsive force is added to support pedestrian *p* avoid other group members.

To summary, the social force model comprises parameters that need to be set at initial simulation time as in Table 1:

**Table 1** – Social-group force model’s parameters

|  |  |  |
| --- | --- | --- |
| **Parameter** | **Component** | **Description** |
|  | Desired Acceleration | Initial desired velocity |
|  | Desired Acceleration | Acceleration time to reach desired speed |
|  | Desired Acceleration | Constant to find maximum velocity |
|  | Repulsive Force with other pedestrians | Angular component |
| *A* | Repulsive Force with other pedestrians | Interaction strength |
| *B* | Repulsive Force with other pedestrians | Interaction range based on distance between *p*, *q* |
| U | Obstacle Force | Obstacle interaction strength |
|  | Simulation | Radii of pedestrian *p* in simulation environment |
|  | Group vision force | The strength of the social interactions between group members |
|  | Group attraction force | The strength of the attraction effects |
|  | Group repulsion force | The repulsion strength between group members |

Social-force based model has possessed a long-life modification period by its author and colleagues for more than a decade in order for simulating the additional factors affecting individual’s acceleration or being easier towards calibration process. However, it almost uses the same parameter distribution to simulate pedestrians inside crowd as in Table 2.

**Table 2** – Social-group force model’s parameter value

|  |  |  |
| --- | --- | --- |
| **Parameter** | **Value** | **Reference** |
| (m/s) | avg. = 1.34, st. dev. = 0.26 | (Helbing, 1995) |
| avg. = 1.3, st. dev. = 0.3 | (Helbing, 2005) |
| (s) | 0.5 | (Helbing, 1995) |
| 1.0 | (Helbing, 2000), (Helbing, 2005) |
|  | 1.3 | (Helbing, 1995), (Helbing, 2005) |
| *A* (m/s2) | 3.0 | (Helbing, 2005) |
| *B* (m) | 0.2 | (Helbing, 2005) |
|  | 0.75 | (Helbing, 2005) |

Through observation, Moussaid found that pedestrians in same group likely move in a line-abreast formation to allow them communicate with each other easily. When crowd density increases, group of pedestrians automatically change its formation into V-shaped or river-like pattern. According to the study, when the model parameter = 0, it shows that group members only try to stick together with no communication rule. When = 4, a V-shaped structure is created.

The authors applied the same value of each parameter in Table 2 and parameters of group force including to all pedestrians inside group to see these patterns. In fact, human group formation is various from V-line, U-like, line-abreast, to river-abreast as in actual observation (Helbing, 2005). However, this model did not mention at which values of parameters other group formations could be created. It also raises a question whether these parameters have to be the same for all group members to establish these structures.

* 1. **Cellular automata model for group behaviour**

Cellular automata-based group behaviour model is the approach relying on of Von Neumann’s idea that divides space into uniform grid or hexagonal cells. At each time *t*, variables at each cell are updated according to a set of local rules or its neighbour cells (Zheng, 2009). Common local rules are moving direction, or avoidance rules. Every cell in the space can be in different states including free, an obstacle, or occupied by a pedestrian. General cellular automate model is formed as formulas 4-6.

|  |  |
| --- | --- |
| where | (4) |
|  | (5) |
|  | (6) |

Every cell has variables of path field, obstacle field, and density field. Path field is to identify distance from current cell to destination cell. Obstacle field indicates for every cell the distance from an obstacle or a wall. Density field is to indicate for each cell the crowd density in the surroundings at the current time step *t.* When running a CA-based pedestrian model, there is several update strategies including parallel update, sequential update, or shuffled sequential update.

To simulate group behaviour, Vizzari (Vizzari, 2013) constructed pedestrians on these defined cells. A pedestrian is represented as a utility-based agent having following attributes:

|  |  |
| --- | --- |
|  | (7) |

where:

* Id: identification number of pedestrian *i*
* GroupId: identification number of group that pedestrian *i* belongs to
* State: represents pedestrian’s current cell that and direction followed in last movement
* Actions: is the set of possible actions to choose an appropriate cell from equation (5) and equation (6).
* Destination: reflects current path field of the cell where pedestrian *i* is in

A utility function was proposed by the author as in equation 8. The function estimates the probability of cell c to allow pedestrian *i* move in to maintain group cohesion at each time step *t*.

|  |  |
| --- | --- |
|  | (8) |

where:

* , , , , , , are model’s parameters for their corresponding functions
* is the goal attraction derived from current cell’s path field and destination cell’s path field
* represents obstacle repulsion from obstacle field of current cell *c* over the maximum distance to obstacles from any cell in grid layout
* represents separation value to allow pedestrian *i* avoid other pedestrians. It is measured by density field of current cell *c* over the predefined maximum density.
* represents whether this cell is the same direction with previous movement of pedestrian
* represents a small probability to allow two pedestrians stay on the same cell.
* represents cohesion value of cell *c* if pedestrian *i* move in towards other group member’s position
* is used in the case of large group which can be separated into sub groups. It represents the cohesion value of current pedestrian toward the largest group.
* is the distance from cell *c* to pedestrian *i*’s current cell position. *d* is only equal to 1 or

Group cohesion degree is then defined as in equation (9) to represent the average distance from each group member to group’s centre of mass. The study used this degree to support pedestrian *i* trade off current goal attraction with group cohesion based on predefined rules.

|  |  |
| --- | --- |
|  | (9) |

The study then measured the correlation between group size and speed in various design layouts. However, this CA-based model only allows pedestrians move in neighbour cells rather than in further cells at each time step. Moreover, it applied the same value of each parameter, , , , , , for whole group members to measure the group speed. Thus, it neglected the heterogeneity in speed, interaction strength, and model parameters of actual group members. The effect of these parameters on group formation was not investigated.

**2.3. Standard Vicsek Model for cohesion behaviour of flocking organisms**

In order to interpret the behaviour of huge flocks of living organisms (flock of birds, fish schools, and bacterium, and human crowd) in the presence of perturbations, a statistical physic approach has been introduced to the flocking by Vicsek (Vicsek, 1995). Nowadays, it has been called as Standard Vicsek Model as suggestion of (Huepe & Aldana, 2008) (Bertin, 2009). The model considers that self-propelled particles represent living flocks, and perturbations are natural consequence of stochastic and deterministic factors affecting the motion of particle. The model is presented in equations 10-11.

|  |  |
| --- | --- |
| + *pertubations* | (10) |
|  | (11) |

The main idea of the model is that at each given time step *t*, particle *i* is usually controlled by interactions with its local neighbours in a constant radius *R* and uncertainty factor perturbations.

Here denotes the averaging of the velocities of neighbours in radius *R*. The expression provides a unit vector pointing in the average direction of motion. The particle *i* also has a constant velocity . In the standard version of the model, Vicsek derived the perturbations factor by adding a random angle to the angle corresponding to the average motion direction of particle i’s neighbourhood. The angel of average motion direction and random angle at time *t* are represented as in equations 12-13.

|  |  |
| --- | --- |
|  | (12) |
|  | (13) |

where and are the x and y coordinates of particle jth’s velocity in the neighbourhood of particle *i*. The perturbation is a random number taken from uniform distribution in the interval [ ]. The randomness of perturbation makes particles have different motion direction from those of others. The velocity was set the same for all birds in flocks. Finally, two control parameters of the model are the density (number of particles in a volume (d is the dimension)), and the level of perturbation (.

In a study of the authors (Crizok & Vicsek, 2000), the average momentum of the particles and the correlation between particles’ velocity directions were investigated when varying model’s parameters including the level of perturbation, the density , and population size.

There is also another approach from the author to investigate the role of model’s parameters (Bhattacharya & Vicsek, 2010) on group cohesion behaviour. This study derived the model in 3D dimensional environment to explore the cohesiveness through the process of landing of bird flocks performing foraging flights. The study explored the heterogeneity in attributes such as the ages, sex, and social status of animals in group or the differences in the perception of external stimuli by assigning to each bird *i* an inherent switching time , such that if the bird begins a flight at time *t*=0, it would decide to land at time t= .This work was to show that the difference in the attributes implied the difference in energy reserve to maintain an altitude. ’s was selected from a Gaussian distribution with a given standard deviation . The study then investigated quantitatively the fraction of birds not landed yet as time *t* progresses when setting to different values. However, the model’s parameters , , were set the same for all birds.( = 2.0, , *R*=2.0, *v*= 0.01).

In summary, standard Vicsek model used the particle-based approach to understand flocking organisms. The author’s proposed studies investigated collective behaviour when varying model’s parameters, adding a new constraint for landing period of individual group members to simulate the heterogeneity of group members. However, these studies have yet explored collective behaviour when considering individual group members have different parameter distributions in these parameters.

1. **Problem Statement**

Modelling human group cohesion behaviour is important since it represents the effect of groups on flow rate measurement and the change of group’s space occupation. Through literature review in section 2, group cohesion models are mainly categorized into three models including the force-based model, and the cellular automata model, and the standard Vicsek model.

Current group force model and cellular automata model make assumption that populations are homogeneous. According to parameters of social force model (parameters in Tables 1 and 2, and parameters of group force ) and automata model (parameters in equation 8), these authors set the same parameter values for all pedestrians. These two models almost investigate group speed, group formation, and group cohesion degree when varying group population size. Considering group members are homogeneous is not true for an actual group which contains different members in age whose physical attributes such as speed, interaction strength are different (Daamen & Hoogendoorn, 2012). Thus, this limitation makes modellers and simulation software’s end users simulate inaccurately different group members.

Standard Vicsek model relies on particle-based approach to simulate the cohesiveness of flocking organisms. Vicsek and colleagues explore the average direction of flocks and velocity correlation of group members when model’s control parameters (interaction radius, random noise constraint) vary. However, these studies still consider that individual group members have the same control parameters. They have not yet explored the behaviour of flock when individual group members have different parameter distributions to those of others.

To summary, the difference of group member’s parameter distributions has not been investigated on flow rate and group cohesion degree measurements of human group behaviour since current studies treat crowds as sets of particles.

**4. Research Question**

Current group cohesion models consider that group members are homogeneous particles through using the same parameter values, even though an actual group contains different group members, who have different parameter distributions to those of others. Thus, this PhD research aims to explore the heterogeneity of group members’ initial parameters in these models by providing questions.

1. What is the effect of setting different parameter distributions for group members on the measurement of group cohesion models?

* 1. What is the difference in flow rates between setting different parameter distributions and averaging out parameter distribution for simulating different pedestrian types?
  2. How do group member’s parameter distributions affect flow rate when group members interact with out-group pedestrians?
  3. How does group cohesion degree change when group member’s parameter distributions vary?

1. **Research methodology**

This section presents the research methodology to resolve the proposed questions. The main question is to explore the impact of group member’s parameters on flow rate and group cohesion degree when group members maintain cohesion behaviour.

**Question 1**: What is the difference in flow rates between setting different parameter distributions and averaging out parameter distribution for simulating different pedestrian types?

Since social-force model and group-force model keep the same parameter values for group members, first work in this question is to investigate whether setting different parameter distributions and averaging out parameters distributions for pedestrian types generate the same flow rates. This work is to examine the viability of setting different parameter distributions on crowd of pedestrians moving individually without taken into account group force.

According to a recent calibration study (Daamen & Hoorgedoorn, 2012), it found that different pedestrians, who are different in age groups (children: <14 years old, adults, elders > 60 years old), are different in value distribution of each parameter (desired acceleration, acceleration time, interaction strength, and interaction range) as in equations 10-13. Thus, a hypothesis testing is applied in the original force model to measure flow rates of two prototypes. The first prototype uses the different parameter distributions to simulate pedestrian types. The second prototype averages out the same parameter distribution for pedestrian types. Escape rates and blockage frequency measurement of two prototypes are investigated.

|  |  |
| --- | --- |
|  | (10) |
|  | (11) |
|  | (12) |
|  | (13) |

After measuring two prototype, group force model is simulated to measure the impact of each group member’s parameter settings.

**Question 2**: How do group member’s parameters affect flow rate when group members interact with out-group pedestrians?

This sub question considers a group of pedestrians (called as group *A*) are moving towards a defined goal and maintaining group’s centre of mass, and another crowd (called as crowd *B*) of pedestrians moving individually towards the goal without influenced by social group force. This sub question considers two scenario types. The first type is evacuation scenario. The last one is the scenario of moving pedestrians along a corridor.

This sub question aims to understand the effect of how a group becomes obstacle for out-group pedestrians when it maintains group cohesion based on group member’s parameters. Figure 2 summarized proposed methodology for this work.

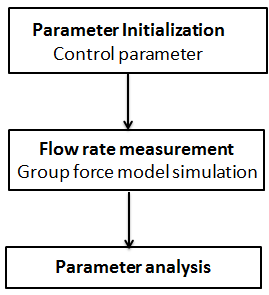


Figure 2. The architecture of investigating parameter distributions on flow rate of evacuation and corridor scenarios

Parameter initialization phase aims to generate initial parameter values for the different group member types in group *A* on the parameters of desired acceleration, acceleration time, interaction strength, and interaction range. This phase only samples at the parameter or the combination of multiple parameters being investigated. At each parameter control, different parameter distributions of group member types are generated from a base distribution of a specific group member type as in equation 14-15. This work is to reduce the complication for handling the control parameter.

|  |  |
| --- | --- |
|  | (14) |
|  | (15) |

where , represent distribution of the control parameter *c* on specific group member type, and , , are model’s coefficient parameters

Social group force model is then simulated to measure flow rates in different simulation environments of evacuation scenario and flow motions. Each simulation environment will also consider both of deterministic model or non-deterministic model by adding random noise taken from a uniform distribution. With the control parameters and their distributions identified in previous phase, each simulation is sampled repeatedly on the distributions.

Parameter analysis phase investigates whether individual control parameter affect flow rate and the interaction of control parameters on flow rate based on the analysis of variance (ANOVA). The change of flow rates is also investigated when varying these control parameters to determine areas in which flow rates change smoothly or discontinuous. This change is also investigated through the velocity correlation and the initial placement of group members.

**Question 3:** How does group cohesion degree change when group member’s parameters vary?

By applying the architecture of investigating group member’s parameters denoted in Figure 2, this sub question aims to understand how spatial occupation of groups vary when groups interact with out-group pedestrians. Group’s spatial occupation is important since it affects movement direction of out-group pedestrians and the prediction of empty space.

In social group force model (Moussaid & Helbing, 2010) represented in literature review, the authors haven’t yet explored the role of group force parameters on individual group members. Thus this question aims at understanding the impact of setting different parameter distributions for group members on group cohesion degree at different values of group force parameters.

* What is the impact of group force parameters on group cohesion degree?

For each control parameter, a scanning parameter space is performed on each group force parameter to understand at which their values, following criteria are emerged:

* group cohesion degree changes smoothly or discontinuous
* group’s spatial organization changes in the same group cohesion degree

It aims to determine areas having the same criteria on two-dimensional space of each pair of group force parameters when varying parameter values in horizontal and vertical directions.

The relationship between each group force parameter and group cohesion degree is investigated through ANCOVA approach. The interaction effect of each pair of group force parameters on group cohesion degree is also studied through ANOVA. Finally, the analysis is compared with the approach using the average distribution to simulate group members.

* How does group cohesion degree change when group interacts with static obstacles?

This work aims to understand how group members react through the change of group cohesion degree when facing obstacles. At each control parameter for group members and the values of group force parameters , simulations are constructed to investigate following criteria:

* group cohesion degree changes smoothly or disordered
* the change of group structure
* group is split and merged by itself
* the change of each cell’s density

In fact, group often split up in large group when facing obstacles through the observation of the study (Reuter, 2012). Thus, this work enables modellers predict free and occupied space when group dynamically change its behaviour.

**6. Research project’s contribution and challenges**

**6.1. Research project’s contribution**

Modelling group cohesion is important since it affects flow rate measurement in both of evacuation and normal scenarios and predicts spatial occupation. This study will provide a detailed understanding of the impact of individual group member’s parameters on group cohesion models. It will enable:

* Modellers understand possible impacts of group cohesion behaviour on flow rate measurement according to different parameter settings of group members when testing different design layouts.
* Event organizers can assess different evacuation strategies in simulate environment via flow rate measurement when simulating with the group behaviour.
* Event organizers can represent the change of spatial occupation of groups containing different members. This works helps to predict empty space in real time and restore the order of crowd before deteriorative situations can occur.

**6.2. Research project’s challenges**

The parameter distributions of group member types rely on base distributions. The sampling time for these distributions are also finite. Thus, this limitation makes the investigation of parameter’s effects might not sufficiently to cover whole parameter values of pedestrians in reality. Moreover, other pedestrian types in reality such as wheel-chair or injured pedestrians also have not been investigated on this area. It is caused by the fact that collecting data of these pedestrians in reality faces ethic problems. Consequently, it becomes questionable to understand distribution types of these pedestrian types. Thus, a general algorithm that can generate various parameter distributions is important to explore the possible heterogeneity of pedestrian types rather than considering pedestrian type’s distributions are normal and generating them from a base distribution.

1. **Research progress**

This section presents current working progress which uses the proposed methodology to resolve research questions of section 4. Current work is separated into three sub sections. The first section is the experimental setups and results to answer the first question. The second section includes current simulation design for the second question. Finally, the research timeline in the last section is to represent continuous phases to resolve the questions 2, 3 on time during the rest time of this study.

**7.1. The impact of setting different parameter distributions for pedestrian types**

Exploring the difference in escape rates between setting different parameter distributions and averaging out the same parameter distribution for pedestrian types become a crucial step to go further of this study.

**7.1.1 Parameter distribution initialization for pedestrian types**

According to the calibration study (Daamen & Hoorgedoorn, 2012), parameters including desired acceleration , acceleration time , interaction strength , and interaction range in Table 2 are different between pedestrian types of children (to age 14), adults, and elders (age 65 and older) in emergency situation. Elderly people are more aggressively to walk with their desired speed than children do. For the interaction strength parameter, the strength of children is strongest comparing to those values between adults and elderly in a population with a large heterogeneity. In the last parameter, children have the lowest value; it implies that the interaction force affecting children can be easier changed by distance than it does on elders and adults. However, the study also mentioned that the standard deviation of each pedestrian type’s parameters was not stable. It was due to the fact that the study was calibrated in various simulated scenarios which involves different percentages of these pedestrian types. Thus, in this study we apply both two approaches including:

|  |  |
| --- | --- |
| *SD*1 : | (16) |
| *SD*2 : , , | (17) |
| where c is control parameter in *S* = {, , , }  k: is base parameter, k = 0.1 |  |

Tables 3, 4 represents parameter distributions for pedestrian types on these approaches based on common values taken from Table 2 of the original social force model.

**Table 3** –Parameter distributions for three pedestrian types in *SD*1 approach

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Social Force Parameters** | **Pedestrian type’s parameters** | | | | | |
| **Children** | | **Adults** | | **Elders** | |
| **Avg.** | **Std.** | **Avg.** | **Std.** | **Avg.** | **Std.** |
| (m/s) | 1.6 | 0.13 | 1.34 | 0.13 | 1.1 | 0.13 |
| (s) | 1.3 | 0.09 | 1.0 | 0.09 | 0.5 | 0.09 |
| ***A***(m/s2) | 4.0 | 0.3 | 3.0 | 0.3 | 2.5 | 0.3 |
| ***B***(m) | 0.15 | 0.02 | 0.3 | 0.02 | 0.2 | 0.02 |

**Table 4** –Parameter distributions for three pedestrian types in *SD*2 approach

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Social Force Parameters** | **Pedestrian type’s parameters** | | | | | |
| **Children** | | **Adults** | | **Elders** | |
| **Avg.** | **Std.** | **Avg.** | **Std.** | **Avg.** | **Std.** |
| (m/s) | 1.7 | 0.17 | 1.3 | 0.13 | 0.9 | 0.09 |
| (s) | 1.3 | 0.13 | 1.0 | 0.1 | 0.5 | 0.05 |
| ***A***(m/s2) | 4.0 | 0.4 | 3.0 | 0.3 | 2.0 | 0.2 |
| ***B***(m) | 0.13 | 0.013 | 0.3 | 0.03 | 0.2 | 0.02 |

Mean values in Table 4 aim to increase the difference between children and elders as the analysis from the calibration study (Daamen & Hoorgedoorn, 2012). By averaging out above parameter distributions for pedestrian types, average prototypes are generated from distributions as below. Prototype level *k* is constrained with conditions of and .

|  |  |
| --- | --- |
| ***Paverage*:** , = | (16) |
| ***Paverage level k***  where, | (17) |
|  | (18) |
|  | (19) |
| ***P uniform level k*** : , | (20) |

where *N* is population size, *c* is control parameter

**7.1.2 Simulation Techniques**

Our simulation is developed with following configuration. Nomad and social force models are implemented on C library for performance purpose.

* Python version 3.4.1
* Numpy library version 1.8.1 is used to generate Gauss distribution for pedestrian’s parameter values.
* Matplotlib library version 1.3.1 is used to plot our measuring results.
* Pygame engine version 1.9 to visualize obstacles and update pedestrian’s position with a frame rate of 100 fps.

The simulation allows pedestrians start at a specific area and move to reach the predefined target. We use Euler’s method to update new velocity and position of each pedestrian as in equations 20-21.

|  |  |
| --- | --- |
|  | (20) |
| V( | (21) |

where *p* is the position, *V* is the velocity, *a* is the total combinatorial acceleration given by Nomad model in equation (3) or total force given by force model in equation (7). is the time step and set 0.01second to perform real-time crowd modelling.

Cartesian coordinator system is applied on Pygame’s screen with a pixel factor to simulate the pixel number per meter. *O*(0,0) root coordinator is aligned at the centre of simulation screen.

**7.1.3 Simulation Scenarios**

A population size N =70 pedestrians in which pedestrian types have the same percentages is performed in this experiment. We design obstacle walls for exit gate with following information in Figures 3. To verify our simulation implementation suit to the crowd phenomena capabilities of social-force model, we reproduced efficiently faster-is-slower effect in unidirectional flow when pedestrians escape a bottleneck from (Helbing, 2000), and phenomena including lane formation, and freeze-by-heating effect in bidirectional flow from (Helbing, 2005).

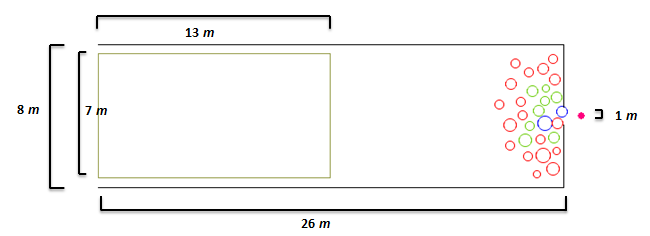


Figure 3. Unidirectional flow simulation for social force model

A yellow-start area is designed sufficiently to simulate the maximum population number up to 70 pedestrians (with pedestrian’s meanradii=0.3 and stdradii=*0.05*). A replication mode is also developed to allow verifying blockage phenomena of each simulation time.

**7.1.4 Escape rate and blockage frequency analysis**

For each approach considering either the same or different standard deviations for parameter distribution of pedestrian types in *SD*1 and *SD*2 , average cut-off based prototypes are investigated at level 3 (*average lv3*), and 1 (*average lv1*). Uniform cut-off based prototypes are also performed at these levels, *uniform lv3* and *uniform lv1*. Parameter distributions of three pedestrian types are sampled 10 times in which each sampling time is simulated 20 times. This work is to investigate different possible parameter values placements of pedestrians in simulation environment. Figures 4 and 5 shows parameter distributions of *SD*1,  *SD*2 at one sampling time on interaction strength *A* parameter.

|  |
| --- |
|  |

Figure 4. Parameter distributions of *SD*1 on six prototypes including

*Pdifferential, Paverage, Paverage lv3, Paverage lv1, Puniform lv3, Puniform lv1* at interaction strength *A* parameter at one sampling time

|  |
| --- |
|  |

Figure 5. Parameter distributions of *SD*2 on six prototypes including

*Pdifferential, Paverage, Paverage lv3, Paverage lv1, Puniform lv3, Puniform lv1* at interaction strength *A* parameter at one sampling time

During simulation duration of 100 seconds, escape number and time are monitored. Escape rate is measured by the last escape time of crowd over the total pedestrian have been escaped. This measurement is to remove the influence of counting escape rate by total population number. Figures 6, 7, 8 present escape number, escape time, and escape rates of the approach *SD*1.

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| Figure 6. Escape number of six prototypes in *SD*1 of the population size N= 70 |

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| Figure 7. Escape time of six prototypes in *SD*1 of the population size N= 70 |

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| Figure 8. Escape rate of six prototypes in *SD*1 of the population size N= 70 |

Figures 9, 10, 11 present escape number, escape time, and escape rates of the approach *SD*2.

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| Figure 9. Escape number of six prototypes in *SD*2 of the population size N= 70 |
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| Figure 10. Escape time of six prototypes in *SD*2 of the population size N= 70 |

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| Figure 11. Escape rate of six prototypes in *SD2* of the population size N= 70 |

Through the observation, the Prototypedifferential, which uses different parameter distributions for pedestrian types, generates highest escape rates comparing to other prototypes. Moreover, average-based prototypes have higher escape rate than uniform-based prototypes.

Figures 11, 12 present blockage frequencies of these two approaches *SD*1, *SD*2.

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| Figure 11. Blockage frequencies of the approach *SD*1 over 200 simulation times |
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| Figure 12. Blockage frequencies of six prototypes in *SD*2 of the population size N= 70 |

**7.2. Social group force simulation**

**7.3. Research Timeline**

1. **Coursework and professional development**

As required from our faculty, I completed the course FIT 5143 in the first semester 2015. I am attending the course FIT6021 from 21 July, 2015. I also completed 116 research training hours as in Table 3.

**Table 3**- List of professional development undertaken

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| --- | --- |
| **Activity** | **Hours counted towards coursework goal** |
| Faculty Induction | 4 |
| Research Integrity | 12 |
| FIT 5143 Course | 48 |
| FIT 6021 |  |
| FIT 4012 | 15 |
| Monash Seminar/workshop attendance | 22 |
| Participation at Monash Bootcamp Commercialisation workshop in the year 2015 | 15 |

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