**THE EFFECTS OF GROUP MEMBER’S PARAMETERS ON HUMAN CROWD MODELLING**

1. **Introduction**

Since over 70% of the world population is predicted to live in cities by 2050 (Weidmann, 2012), rapid urbanization and population growth will be inevitable challenges in the effort of planning infrastructure, estimating traffic needs and capacities, and increasing the safety of pedestrians. With the increase in the number of public events and the number of accidents during these events since the crush disaster happened at the Station Nightclub, USA (2003) (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 order to understand and simulate behaviours which can emerge in both normal and emergency situations such as groups of pedestrians moving with or competing 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 observation of coherently flying objects. The behaviour has been 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 constructed to understand group cohesion behaviour such as the cellular automata model, the social-force based model, the standard Vicsek model. These models mainly investigate how model’s outputs which are group’s formation, cohesion degree, and speed change when group population size varies, or explore the collective behaviour of flocking organisms when varying arbitrarily model’s parameters. However, they have not investigated systematically the effect of group member’s parameters on the model’s outputs; specifically, the most influential parameters which control group information have not been explored. Consequently, the impact of group cohesion behaviour on flow rate which is a crucial measurement of crowd modelling also has not been studied. Therefore, this PhD study aims to resolve these two research gaps by using systematic analysis methods and proposed simulation scenarios.

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

1. **Literature Review**

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

* 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 1-3.

|  |  |
| --- | --- |
| where | (1) |
|  | (2) |
|  | (3) |

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:

|  |  |
| --- | --- |
|  | (4) |

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 (3).
* Destination: reflects current path field of the cell where pedestrian *i* is in

A utility function was proposed by the author as in equation 5. The function estimates the probability of cell c to allow pedestrian *i* move in to maintain group cohesion at each time step *t*.

|  |  |
| --- | --- |
|  | (5) |

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 (6) 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.

|  |  |
| --- | --- |
|  | (6) |

The study then measured the correlation between group size and group cohesion 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. It applied the same value of each parameter, , , , , , for whole group members. Group speed and cohesion degree are investigated when group population size varies. However, the effect of these parameters on group degree and the impact of group cohesion behaviour on flow rate measurement were not investigated.

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

Moussaid, Helbing and colleagues (Moussaid, 2010) created the social group model based on the social-force model (Helbing & Vicsek & Molnar, 1995, 2000). The social group model (equation 7-8) 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 9.

|  |  |
| --- | --- |
|  | (7) |
| = | (8) |
|  |  |

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

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



**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 to avoid overlap each other |

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 actual observation, Moussaid found that pedestrians in the 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 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. Similar with CA-based model, the authors of social-group force models have not investigated the effect of member’s parameters (e.g. , , *A, B)* on group speed and formation. They only studied how these information change according to different group population sizes.

**2.3. Standard Vicsek model for understanding 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 arbitrarily, adding a new constraint for landing period of individual group members to simulate the heterogeneity of group members. However, these studies have not yet explored systematically the effect of parameters and the most influential parameters on collective behaviour. Moreover, these studies also have not yet considered flock of individual group members, who have different parameter distributions to those of others 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 the literature review in section 2, understanding group cohesion behaviour is mainly categorized into three models including the cellular automata-based model, the force-based model, and the standard Vicsek model.

The cellular automata-based and force-based models almost investigate model’s outputs which are group’s speed, formation and group cohesion degree when group population size varies. They have not yet explored the effect of member’s parameters on the model’s outputs. The most related work to the understanding that effect is Vicsek’s studies. 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) are varied. However, they also have not yet explored systematically how group member’s parameters contribute to the uncertainty of the model’s outputs, and investigated the most influential parameters controlling group behaviour. Moreover, the impact of group cohesion behaviour on flow rate has not been investigated in current group cohesion models when group members maintain their cohesiveness. Flow rate is an important observation measure for human crowd modelling since it is used to assess design layouts and evacuation strategies in simulation environments (Shiwakoti, 2014), (Cheng, 2014).

To summary, the impact of group member’s initial parameters on group cohesion model’s outputs and the impact of group cohesion behaviour on flow rate have not been investigated. Understanding the role of parameters in these models and possible group behaviour can be occurred by parameter values are important for crowd modelling to improve calibration process and real-time prediction’s performance respectively. They also enable live-event organizers understand the change of flow rates and occupied space according to group cohesion behaviour.

Exploring the impact of group member’s parameters should consider group members have either the same scalar parameter values as previous studies have performed or different parameter distributions to those of others. In fact, an actual group contains different members in age (children < 14 years old, adults, elders > 65 years old) whose physical attribute distributions including desired speed, acceleration time, interaction strength, interaction range are different to those of others (Daamen & Hoogendoorn, 2012).

**4. Research Question**

This PhD research aims to explore the effect of member’s parameters on group cohesiveness through social-group force model and the impact of group cohesiveness on flow rate measurement in simulation scenarios. Following research questions summarize this aim.

* 1. What is the impact of group member’s parameters on group cohesion behaviour when group contains members having the same scalar value on these parameters?
  2. How does group cohesion behaviour affect flow rate measurement?
  3. What is the impact of group member’s parameters on group cohesion behaviour and flow rate measurement when considering group member are heterogeneous in parameter distributions?

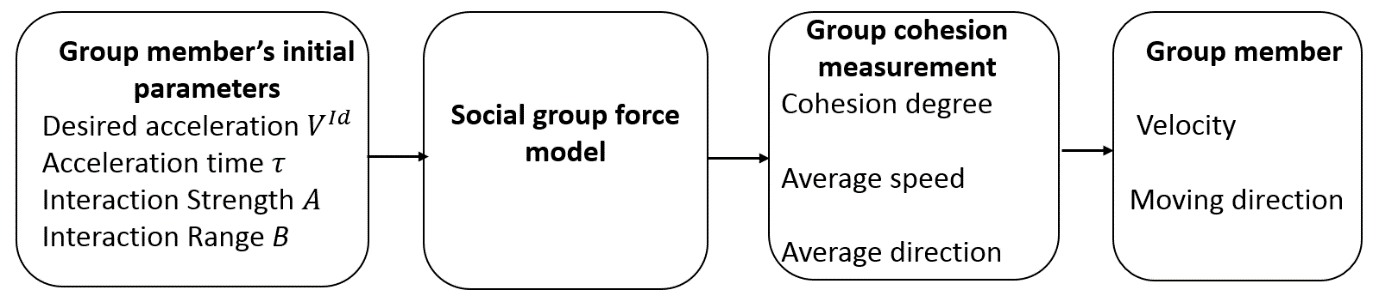
The first two questions provide a fundamental understanding for the question 3. Because of its importance and time constraint for the rest of this PhD period, this study focuses on the first two questions and considers the question 3 as optional.

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 crowd’s flow rates when group members maintain cohesion behaviour.

**Question 1**: What is the impact of group member’s parameters on group cohesion behaviour when group contains members having the same scalar value on these parameters?

This sub question aims to give a comprehensive understanding of the role of group member’s parameters in human cohesion behaviour. The relationship between group member’s parameters and group cohesion measurement is proposed as in Figure 2.



**Fig 2**. The methodology to understand the effect of group member’s parameter on human group cohesiveness behaviour

Social-group force model is used in this study since its original social force model (Helbing, Vicsek, Molnar, 2000) sufficiently simulates human crowd’s self-organization phenomena in nature (e.g. lane formation, stop-and-go waves, bottleneck, turbulence phenomena) comparing to other crowd models (Hoogendoorn, 2013). Moreover, social force model was also co-invented by Vicsek, who invented the Standard Vicsek model, to design a particular model for simulating human movement.

Four group member’s parameters including desired acceleration , acceleration time , interaction strength and interaction range *B* are investigated since they are initial parameters of pedestrians in the model. Moreover, they also are different between group members in ages through the recent calibration study in emergency scenarios (Daamen & Hoogendoorn, 2012).

Group cohesiveness is measured popularly by three factors including group cohesion degree, group average speed, and group average moving direction through major studies in the research field (Crizok & Vicsek, 2000), (Vicsek & Crizok, 1995), (Ballerini, 2008). These factors are represented in equations (6), and (12-13). These factors are also particularly important for human group simulation because they support to represent occupied space for evacuation strategies and modelling collision avoidance of individual pedestrians when facing groups ahead.

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

where *N* is group population size

This question is divided into three smaller questions which aim to explore parameter-cohesiveness relationship. The first question is to describe the range of possible model’s outputs of the three factors given by a set of inputs at the four model’s parameters where the parameters have uncertainty. Through providing the distributions of resulting outputs, it aims to support the predictive capacity of the model on human group cohesion behaviour. The second question aims to identify the key input parameters that contribute the most to the model’s predictive uncertainty. By identifying the most influential parameters, it aims to improve the predicative capacity of the model by refining our estimates for those parameters. It also aims to help us explore the effects of simultaneous parameter variations. The last question helps to understand how different group cohesion factors affect individual group members.

* How do parameters of desired acceleration , acceleration time , interaction strength and interaction range *B* affect the model’s outputs?

This work relates to uncertainty analysis (UA) which aims to study how the uncertainties in the input parameters can be mapped to the uncertainties in the outputs. The uncertainty analysis methodology have been applied widely in biological systems (Marino, 2008), water resource models (Loucks, 2005), traffic emission models (Eriksson, 2007), and risk management models (Hayes, 2011). This study investigates the effect of above four parameters by using Monte Carlos simulation (MCS). For a model with k parameter inputs **x** =[x1, x2, x3,…, xk], MCS methodology involves the following steps (Saltelli, 2000a):

1. Define distributions *D1, D2, D3, …, Dk*for the input **x**

2. Generate a sample of size *N* ***x1****,* ***x2****,* ***x3****, …,* ***xN*** from the defined distributions

3. Run the model for each element in the input sample to obtain model’s outputs **y(*xi*)**, *i*= 1,2,3,…, *N*

4. Quantify and display the uncertainty in the model outputs

5. Explore the mapping between uncertain inputs and the output uncertainty

The output of MCS analysis is sensitive to the input distributions. The first step which characterises those distributions is the most important part in this technique as these distributions determine both the uncertainty **y** and the sensitivity of the elements of **y** to the elements of **x** (Saltelli, 2000b) (Helton, 2006). This step then considers two approaches: 1) define the simultaneously average distributions for four parameters 2) vary one parameter-at-a-time (OAT) which leaves fixed parameter values for remaining parameters by using their commonly values in Table 2.

In the second step, both random sampling and Latin hypercube sampling (LHS) are studied. LHS sampling procedure, which ensures the entire bins of each input are sampled, is also investigated since it has been shown to be more efficient than random sampling procedure (Helton and Davis, 2003) and used in the analysis of a number of biological systems.

In the third step, once the input samples have been generated for group members, social-group force model is simulated and the results of group cohesion measurement are stored over the time.

In the fourth step, group cohesion measures including scalar outputs of group cohesion degree, average velocity, and average direction are summarised by the mean value and variance. More information is then obtained by plotting cumulative distribution function (CDF) of the outputs. CDFs are then extracted at different time slices to obtain a picture of the output uncertainty.

The last step is to explore the effect of individual parameters on the model outputs. This study uses following techniques including correlation analysis, regression analysis, and variance-based analysis, which are represented respectively as follows:

* Correlation presents a measure of the strength of linear relationship between each model’s parameter *j* with model’s outputs *y*. It is measured by equations 14-15. In time-varying model, partial rank correlation coefficients are investigated on continuous time slices.

|  |  |
| --- | --- |
|  | (14) |
| where  , | (15) |

* Regression analysis provides a representation of the relationship between *y* and multiple x*j’s* as equations 16-17.

|  |  |
| --- | --- |
|  | (16) |
| where the regression coefficients are determined such that the following sum  is minimized | (17) |

* Variance-based analysis deal when non-linear relationship of parameter *j* and model’s output *y*. It partitions total output variance and identifies the amount of output’s variation according to the uncertainty in the parameters. Two main approaches of Fourier amplitude sensitivity test (FAST) (Cukier, 1978) and its extension (eFAST) (Saltelli, 1999), which explore the parameters on frequency space, are investigated.
* What is the most influential parameter used to control group cohesion behaviour in time-dependent outputs?

This work relates to sensitivity analysis (SA) which is performed to describe how sensitive the model’s output are to the variation of individual input parameters. It helps to determine which parameter lead the majority of the variation in the output. Sensitivity analysis has been used widely in research fields of biological systems (Sumner, 2012), (Hetherington, 2006), software engineering (Williams, 2012), (Wagner, 2007), cellular signalling (Hu and Yuan, 2006) to enhance the understanding of complex computational models, seeking inputs which have substantial effect on particular outputs, constructing an emulator/reduced model.

In this study, ranking the most sensitive parameters and their interaction effect with other parameters are performed by Sobol variance-based approach and Morris’ screening design. Sobol method is based on the decomposition of the model’s output into terms of increasing dimensionality and then compute the Sobol indices (the contribution) of each parameter to the variance of model output. Morris scanning approach is based on OAT in which the investigating parameter is varied by small amount around its nominal point to identify the model behaviour in that region. Morris approach then repeats on different nominal points to measure the different outcomes. These two methods are presented as equations (18), and (19) respectively as follows:

* Sobol approach: Given a model of the form *y(t)=f(u,****P****,t)* where model’s output *y(t)* is a set of curves describing the variation in the model output over time, *u* is external model input, and a set of *k* parameters represents model’s considerable parameters (P=( *p1*, *p2*, *p3*,…, *pk*)). The function *f* can be represented as:

|  |  |
| --- | --- |
| + …. + | (18) |

* Morris scanning approach: consider *y(P)* is a the output of the model at parameter point ***P*** where P is vector of parameter values at ( *p1*, *p2*, *p3*,…, *pk*). The Morris method defines the elementary effect of ith parameter at P as:

|  |  |
| --- | --- |
|  | (19) |

where is selected such that P + is still in the set of allowable values for parameter *k*

The ranking of influential parameters through two approaches is presented and the most influential parameters is then applied in simulation to visualize how group cohesion changes according the parameters.

* How does group cohesion behaviour affect group member’s velocity and direction over the time?

This question investigates group member’s average speed, variance in speed, turning direction according to his initial parameters. Two prototypes are compared on his initial parameters including moving individually, and moving with group. It is used to hypothesize that when in groups, individuals would behave more uniformly together. This work has been done in the research of schooling fishes (Herbert-Read, 2012) through linear mixed-effects model to assess the effect of context (parameters of other group members on the ranking of influential parameters). Other information such as panic level (the variance of actual speed over desired speed) is also investigated.

**Question 2**: How does group cohesion behaviour affect flow rates?

This question aims to investigate the impact of group cohesion behaviour on flow rates in various simulation scenarios of corridors and evacuations comparing to individual behaviour. This work is based on parameter selections which produces different group cohesion behaviour in Question 1.1 and the ranking of influential parameters in Question 1.2. This work is performed to understand the transferring information of group centre of mass can help individual group members avoid effectively obstacles.

* Scenario 1: Move with group comparing to move individually to avoid obstacles.
* Scenario 2: Group members interact with out-group individuals.

Trajectories of individual members are tracked to understand the difference in each scenario. The change of flow rates is also investigated when varying group member’s parameters to determine areas in which flow rates change smoothly or disordered.

**Question 3**: What is the impact of group member’s parameters on group cohesion behaviour and flow rate measurement when considering group member are heterogeneous in parameter distributions?

A recent calibration study (Daamen & Hoogendoorn, 2012) found that different pedestrians in age (children < 14 years old, adults, and elders for those who are higher than 65 years old) have different distributions in individual parameters to those of others in evacuation scenarios. Thus, the initial exploratory step in this study is to investigate which average distribution is appropriate to simulate the heterogeneity in pedestrian types among normal, normal with cut-off constraints, uniform distributions

**6. Research project’s contribution**

This study will enable modellers understand following impacts of member’s parameter settings on group cohesion behaviour. Although calibration studies also help us to understand and find out possible parameters of real-world pedestrians; they only contain a finite number of actual pedestrians:

* + which parameter contribute most to the variance of group cohesion behaviour
  + how group cohesion behaviour can varies possibly
  + how group cohesion affect individual group members
  + the impact of group cohesion behaviour on flow rate measurement which has not been explored by previous human crowd models

Understanding the role and interaction effect of parameters on the model’s outputs helps to improve the performance of real-time prediction systems based on these models by:

* + Refining and concentrating on the most influential parameters for real-time extraction systems in studies (Mazzon, 2013) (Moore, 2011).
  + Predicting empty and occupied space for evacuation plan and crowd’s possible behaviour from known parameter distributions of pedestrian types in crowd before deteriorative situations can occur.

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).

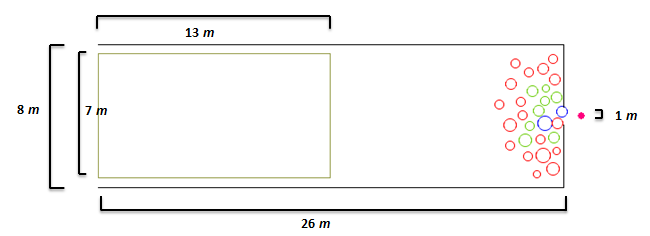


Figure 3. Unidirectional flow simulation for social force model

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.

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

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

|  |
| --- |
|  |
| 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.

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

|  |
| --- |
|  |
| 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.

|  |
| --- |
|  |
| Figure 11. Blockage frequencies of the approach *SD*1 over 200 simulation times |
|  |
| 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**

Draw table here as in Figure 13 –hard paper

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

|  |  |
| --- | --- |
| **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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