Comparing Simulations of Pedestrian Motion
MPhys Project Report

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Project in collaboration with Paul Vriend

Abstract

We investigate the difference between cellular automaton based models and social forces model in the simulation of pedestrian dynamics. Recent findings with a cellular automaton of the effect of communication on the evacuation behaviour of pedestrians were reproduced. The overall trend of increasing evacuation efficiency was confirmed. However, for a social forces model an increase in communication leads to increased evacuation efficiency while in cellular automaton model this is not always the case. A second point of comparison was lane formation in a corridor with counter flowing stream of pedestrians. The social forces model reproduced this phenomena but the order parameters employed in cellular automaton models are unable to detect these lanes. Several order parameters were investigated but no satisfying method of measurement was found.

1 Introduction

The repeat occurrences of mass panics that lead to the death of many, such as the 1990 Mecca panic, which killed over 100 people, is a strong motivation for a robust understanding of crowd dynamics. As such simulations cannot be recreated experimentally, a realistic model is necessary to investigate such effects. Numerous different models exist and understanding the limitations and realism of the different existing models is the aim of this project. Specifically, the effect of communication on pedestrian evacuation was investigated as well as lane formation in counter flowing streams of pedestrians in a corridor.

The case for an investigation by physicists is twofold. On one hand, physics has been concerned with particle motion since its inception and all the approaches that exist in traditional physics have been successfully applied to pedestrian motion. Pedestrians have been modelled with Newton equations or stochastically with Langerin and Fokker-Planck equations as well as fluids. On the other hand, this problem seems to be well suited to a reductionist, physicist approach. It is a complex system in which it is possible to reproduce emergent phenomena with a few fundamental rules. Emergent means that the observed phenomena are not build into the system but appear because of the complex interaction.

Pedestrian dynamics is a complex system involving interactions between individuals. These occur over a range of distances; a pedestrian will interact more strongly with another pedestrian five meters away but on a collision course than another pedestrian half a meter away in parallel motion. Through these interactions arise several self-organization phenomena (such as lane formation) and only a few models exist that reproduce empirically observed behaviour accurately. Strictly speaking the term ”pedestrian” refers to a person and ”particle” is the representation of a person in a model. An ”agent” is a particle in a model that acts autonomously e.g. communicates and makes decisions.

In the remainder of section 1 the empirical observations and approaches of simulating pedestrian dynamics are described. In section 2 the model used in our simulation is detailed and in sections 3 and 4 we present our results. In section 5 we present a scenario we hope to use in the 2nd Semester and in section 6 we conclude with a summary and an outlook on future work.

1.1 Empirical observations of Pedestrian Dynamics

For the motion of pedestrians, relatively little empirical data exists because of the difficulty of analysing experimental data. A common method of data collection is by analysing video footage. For the case of panics and evacuations almost no empirical data is available due to the unexpected nature of such occurrences.

Pedestrians have a desired walking speed that depends on their purpose, external conditions, sex (men are 10 % faster than woman) and age (older people walk slower) of the walker. Weidmann [1] compiled average values of pedestrian velocity, shown in Table 1. The velocities in crowds follows a Gaussian distribution with a mean of 1.34 m/s and a standard deviation of 0.26 m/s. Pedestrians can accelerate and decelerate almost instantly and have a typical step length of 0.65 m and step frequency of 2 Hz.

Crowds display a large range of collective phenomena, a short discussion of their behaviour under panic conditions will be given here based on the comprehensive treatment in [2, 3, 4]. Crowd stampedes and panics often lead to fatalities. While sometimes the

Sex	$v_i^0[m/s]$	Purpose	$v_i^0[m/s]$
All	1.34	Leisure	1.10
Men	1.41	Shopping	1.16
Women	1.27	Commuting	1.49
		Business	1.61

Table 1: *Data from Weidmann [1] on the average speeds of pedestrians, broken down by sex and by purpose of travel.*

cause, such as a fire, is know at other times these appear without apparent disturbance. Stampedes lead to a breakdown of normal pedestrian behaviour starting with pedestrians trying to move at much higher speeds, pushing and coming into physical contact with other pedestrians. This leads to jams, clogging and uncoordinated crowd movement. Additionally people tend towards mass behaviour and alternative exits are often overlooked. During panics, pedestrians often try to exit it through the entrance they used to enter the building even if other exits are closer [5, 6]. This makes the effect of communication on evacuation dynamics of great interest.

1.2 Modelling Approaches

Motion of pedestrians has been studied since the 1960's . There are numerous methods of modelling pedestrians including cellular automata, AI Models and social forces models.

1.2.1 Cellular Automata

In the Cellular Automata (CA) models, both time and space are discrete. The maximal observed pedestrian density is around $6\ P/m^2$ (where P stands for People). Therefore, a pedestrian occupies around $40 \times 40\ cm^2$ of space giving the cell size of this model. Each cell can then be either full (with a person) or empty and the interaction with the nearest neighbours determine the update rules. The particle in this model wishes to move in a desired direction. If the cell in this direction is free, then the particle moves forward. If it is occupied then it tries to move perpendicular to the direction of motion or diagonal. If several particles try to move to a cell then one is picked randomly.

1.2.2 Floor Field Cellular Automaton

The Floor Field CA model is identical to general CA models with the addition of a floor field. It was inspired by the pheromone trails used by ants to communicate whether they found food on the path they took [2]. The purpose of the floor field is to transform long-range interactions into local effects to enable easier computation. This is more efficient in complex geometries as one does not have to check explicitly whether interactions are blocked by walls.

Space and time are discreet just as in the CA model. However, there is a transition amplitude to every neighbouring cell depending on the floor field that evolves with time. This floor field combines the desired direction, interactions with walls, obstacles and other pedestrians.

On short distances, pedestrian to pedestrian interaction is usually repulsive and implemented by the rule that each cell can only be occupied by a single particle. Over long distances, pedestrian to pedestrian interactions are often attractive i.e. it is advantageous to follow a crowd going in the same direction. This is represented as a local interaction by the floor field. The effects of the infrastructure are shown by the static floor field that is constant. The dynamic floor field is the traces left by pedestrians that influences the motion of subsequent pedestrians and can decay with time.

The transition probability p_{ij} to each neighbouring cell j from the current cell i is given by the contribution from the static (S) and dynamic (D) floor field and the preference matrix P. The preference matrix P can be used to give pedestrians individual speeds and walking directions. The transition probability is then given by

$$p_{ij} = N\ e^{k_D D_{ij}}\ e^{k_S S_{ij}}\ P_{ij}\ (1 - n_{ij})\ O_{ij} \tag{1}$$

where k_D and k_S are the coupling constants to the floor fields and N is a normalization factor that ensures the probability sums to one. The obstacle matrix O_{ij} describes the infrastructure and is zero for forbidden cells such as walls and one for allowed cells. The factor $(1 - n_{ij})$ is the occupation number of the neighbouring cell. For a particles current position, $n_{ii} = 0$ to allow the particle to stay at the same position.

1.2.3 Social-Forces Model

The social forces model is a continuum model based on Newtons equation. As the name implies, the psychological motivation of individuals to move towards their target and avoid collisions are described by "social forces". The origin of these is of psychological rather than physical nature but they are otherwise treated identically. Additionally there are physical forces such as friction between objections and forces opposing compression. This model, proposed by Helbing and Molnár [7] will be the focus of our work and is described in detail in Section 2.1. It will henceforward be referred to as the Helbing Model with no intention of diminishing the contribution of the co-authors.

1.2.4 Fluid Dynamic / Kinetic Models

As pedestrian dynamics have similarities with fluids, some of the earliest approaches were based on kinetic theory, treating pedestrians as a gas. In these models the interactions between the pedestrians are modelled as collision processes with the exchange of momentum and energy. As we are not concerned with such models in this work this will not be discussed in this report but Nishinari *et al* [2] and reference therein extensively review these models.

1.3 Goal of the Project

Our initial goal was to reproduced several recent findings from simulations done with CA models using the more complex Helbing Model. We aim to investigate the differences between simple CA models that aim only to capture the basic phenomenology to the Helbing model that attempts a more detailed description of the underlying processes. We considered two scenarios of pedestrian motion: lane formation and the effect of communication on evacuation.

My main focus has been the effect of communication in pedestrian evacuation based on a paper by Smyrnakis and Galla [8]. In this context the agents use communication to effectively choose one of several exits from a large area such as a bridge. For this reason we refer to this as the bridge scenario. The results of our reproduction are detailed in section 3. My partner, Paul Vriend, focused on the phenomena of lane formation in corridors. Nowak and Schadschneider [9] investigated this phenomena using a floor field CA and serve as the point of comparison to the Helbing Model. The results from this scenario, which we termed corridor scenario, are given in section 4.

2 Reproducing the Helbing Model

2.1 Description of the Model

We have adapted the model Helbing, Farkas and Vicsek proposed in their Nature paper [5]. This model describes the natural tendencies of pedestrians to keep a distance from other people and walls and the wish to reach a target using forces. Each pedestrian i of mass m_i wishes to move in a certain direction $\mathbf{e}_i^0$ with a desired velocity v_i^0 and accordingly accelerates to adjust the actual velocity $\mathbf{v}_i$ in a characteristic time τ_i. At the same time the pedestrian tries to keep a distance from other pedestrians j and walls W. This is represented by the interaction forces $\mathbf{f}_{ij}$ and $\mathbf{f}_{iW}$. The equation of motion is given by

$$m_i \frac{d\mathbf{v}_i}{dt} = m_i \frac{v_i^0(t)\mathbf{e}_i^0(t) - \mathbf{v}_i(t)}{\tau_i} + \sum_{j(\neq i)} \mathbf{f}_{ij} + \sum_W \mathbf{f}_{iW} \tag{2}$$

with the change in position $\mathbf{r}_i(t)$ given by the velocity $\mathbf{v}_i(t) = d\mathbf{r}_i/dt$.

The avoidance of contact between pedestrians i and j is modelled by the force $A_i exp[(r_{ij} - d_{ij})/B_i]\mathbf{n}_{ij}$ where A_i and B_i are constants. The distance between the pedestrian's centre of mass is $d_{ij} = |\mathbf{r}_i - \mathbf{r}_j|$ and the the normalized vector pointing from pedestrian j to i is given by $\mathbf{n}_i j = (\mathbf{r}_i - \mathbf{r}_j)/d_{ij}$. If the distance between them, d_{ij}, is smaller than the sum $r_{ij} = r_i + r_j$ of their individual radii r_i and r_j, the particles are in contact. In this case two additional forces come into play: a "body force" $k(r_{ij} - d_{ij})\mathbf{n}_{ij}$ counteracting compression and a frictional force between the pedestrians $\kappa(r_{ij} - d_{ij})\Delta v_{ij}^t \mathbf{t}_{ij}$ impeding relative tangential motion. The tangential direction is given by $\mathbf{t}_{ij} = (-n_{ij}^2, n_{ij}^2)$ and the tangential velocity difference is $\Delta v_{ij}^t = (v_j - v_i) \cdot \mathbf{t}_{ij}$. In summary, we have

$$\mathbf{f}_{ij} = \{A_i exp[(r_{ij} - d_{ij})/B_i] + kg(r_{ij} - d_{ij})\}\mathbf{n}_{ij} + \kappa g(r_{ij} - d_{ij})\Delta v_{ij}^t \mathbf{t}_{ij} \tag{3}$$

where the function $g(x)$ is zero if the pedestrians do not touch each other and is otherwise equal to its argument x.

The interaction with the walls is treated analogously. The distance to the wall W is d_{iW}, $\mathbf{n}_{iW}$ denotes the direction perpendicular to the wall and $\mathbf{t}_{iW}$ the direction tangential to the wall. The wall force is then given by

$$\mathbf{f}_{iW} = \{A_i exp[(r_i - d_{iW})/B_i] + kg(r_i - d_{iW})\}\mathbf{n}_{iW} + \kappa g(r_i - d_{iW})(\mathbf{v}_i \cdot \mathbf{t}_{iW})\mathbf{t}_{iW} \tag{4}$$

The constants were defined identical to those that Helbing *et al* used: a mass of 80 kg and an acceleration time of $\tau_i = 0.5s$. The constants $A_i = 2 \times 10^3 N$ and $B_i = 0.08m$ are defined such that the models reproduce the distances kept by crowds under normal desired velocities and fit the measured flows through bottlenecks. The parameters $k = 1.2\times 10^5 kgs^{-2}$ and $\kappa = 2.4\times 10^5 kgm^{-1}s^{-1}$ determine the friction and anti-compressional forces in case of contact. To avoid gridlock, some irregularity is introduced into the model by uniformly distributing the radii r_i of the pedestrians in the range [0.25m, 0.35m].

The equations of motions are integrated numerically using the Euler method. Taking an ordinary differential equation of the form $dy/dt = f(t, y(t))$ subject to the initial condition $y(t_0) = y_0$. Let the step size be h which allows us to define time in terms of the initial time t_0 by $t_n = t_0 + nh$. One step of the Euler method from t_n to $t_{n+1} = t_n + h$ is given by

$$y_{n+1} = y_n + hf(t_n, y_n) \quad (5)$$

where y_n is the value of the function at time t_n, i.e. $y_n \approx y(t_n)$. The initial condition in our simulations is the initial position of the pedestrians in the room. These are set by randomly distributing the population of pedestrians over the available area while ensuring that no overlap occurs. The time step h determines the accuracy of the numerical solution. This is a trade off between computational speed and accuracy and we experimentally determined a step size where a further reduction did not alter the behaviour of the simulation.

2.2 Verifying our Model

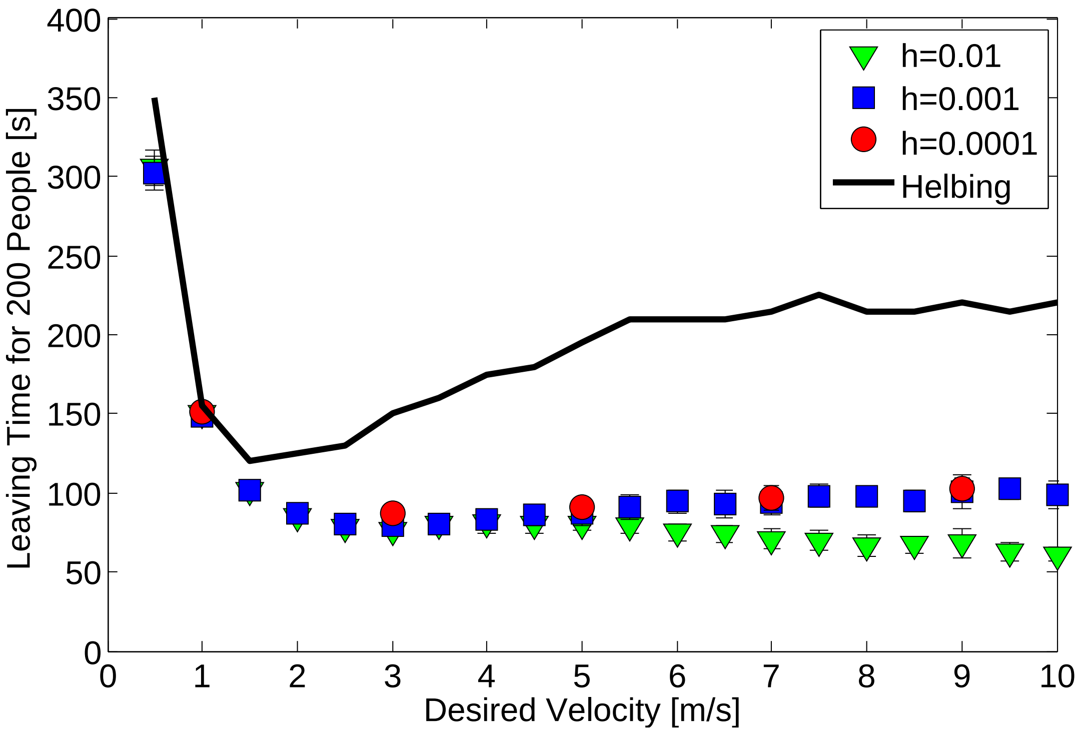


Figure 1: *Leaving time for 200 people from a square room of* 15×15 *meters and a 1 meter wide door. The equations of motion are numerically integrated using the Euler method with a time-step* h *and averaged over 20 runs. The results for simulations with times steps of* $h = 10^{-1}$ *(green triangles),* $h = 10^{-2}$ *(blue square) and* $h = 10^{-3}$ *(red circles) are shown. The results of Helbing* et al *is shown (black lines) [5].*

Helbing *et al* calibrated their model against the experimental observation that 0.73 persons per second pass through a 1m wide door when the desired velocity is $v_i^0 \approx 0.8ms^{-1}$ [1]. When simulating this scenario we found a value of 0.8 ± 0.1 P/s. To ensure that we reproduced the Helbing model we decided to reproduce the "faster-is-slower" effect Helbing *et al* observed when simulating escape from a room: when people wish to move faster through the exit, the increased pressure creates clogging that slows down the rate of escape.

The escape time versus desired velocity from a room of 15×15 meters and a 1 meter wide door is show in Figure 1 [1]. While we reproduce the ”faster-is-slower” effect, it is much less pronounced and our minimum leaving time is lower than that of Helbing *et al*. There is a clear discrepancy between Helbing *et al* results and our result. There are several possible reasons for this discrepancy. For the model to work a velocity cut off is needed. Helbing *et al* describe this in their 2001 paper [10] but made no mention of it in their 2000 paper [5]. The use of a different velocity cut-off could explain the differences in our results. Another possibility is that the graph we used for comparison is a model that includes injury of pedestrians when the force on them exceeds a certain pressure. These injured people change the dynamics of the crowd making a direct comparison invalid. The caption in their 2000 paper is not explicit. While we could not reproduce the exact graph we have reproduced the ”faster-is-slower” effect and fit out data to the the observed rate through an exit 1m wide. Therefore we concluded that out model was working and proceeded to apply this to new scenarios.

2.3 Computational Optimization

Number of Threads	Time for 1000 People [ms]	Time for 2000 People [ms]
1	328	2367
2	229	1005
4	229	961

Table 2: *Optimization of the program for multiple cores. Time taken to perform one time-step. The average of 100 runs is taken using a Intel Q9550 Core 2 Quad.*

Compared to a cellular automaton model, where the number of computations is of the order of the sample size $\mathcal{O}(N)$, in the Helbing Model the computational time is of the order of $\mathcal{O}(N^2)$ as each pedestrian evaluates the force from every other pedestrian. The first step in the project was to choose a programming language to write in, our two main requirements being computational speed and the ease with which graphical output could be generated. We choose Java as it aids the implementation of graphical output and has a comparable speed to native languages such as C++. Java has the added benefit that the code is transportable between Operating Systems without needing any adjustments.

To reduce calculation, a cut-off was introduced. If the distance to a person or a wall is greater than $1.7m$ and hence the force from this object is less than $10^{-3}N$, the force is not calculated as the effect is negligible compared to other forces acting on a pedestrian.

We investigated the speed of calculation compared to read and write to memory. As the force f_{ij} on pedestrian i from pedestrian j is equal and opposite to the force on j, f_{ji}, this can either be calculated twice or be written and read from memory. We found that reading and writing to memory is around 10% slower than calculating the force twice.

Most calculations were done in the undergraduate computer cluster by letting computers run overnight or over weekends. For simulation with 1500 people, the runtime for a single simulation is 5 hours. To collect a data set with 20 trials takes 80 hours, unfeasibly long given the computational resources available to us. As part of the Bridge scenario

[1]Example videos of this and later simulations can be found on http://mphys.herobo.com

(described in Section 3 I implemented the code for parallel computation, allowing it to use more than one core to speed up computation. In Table 2 the run times per time step are shown, using a Intel Q9550 Core 2 Quad. As this CPU has two cores, we expect a large reduction in runtime when using two threads but only negligible reductions when using more than two threads. The simulations for the bridge scenario took a total of ~ 4000 hours.

3 The Bridge Scenario

This scenario is based on a paper by Smyrnakis and Galla [8] in which they investigate the effects of communication and utility-based decision making on evacuation from a room. Several approaches to decision making exist, such as neural networks [11]. These decision making models typically consider information about the area that is being evacuated. Smyrnakis and Galla considered the effect of direct communication between agents on evacuation efficiency.

We replicated the set up and ran simulations with the Helbing Model to investigate whether their results persist with the change of model. The code for this scenario as well as running the simulations was my responsibility while my partner, Paul Vriend, concentrated on the Corridor Scenario. However, throughout we consulted each other on problems and the best approach to the implementation of the code.

3.1 Set Up

Smyrnakis and Galla use a CA model to propagate the particles. Their room has a large central rectangular area 10m x 50m with exits on the shorter sides. On each side there are two exits. The exits on one side have a width of 3.2 meters (L for "larger") while the exits on the other side are of the width of 0.8 meters (S for "smaller"). Once the particles leave the central area they move up or down, depending which exit is closer. A schematic and pictures from an evacuation are shown in Figure 2.

Agents in the main evacuation area use a utility function to assign a utility to each exit and then move towards the exit with the highest utility. The default utility function is based on the expected time to reach a certain exit, i.e. agents move to the closest exit. Certain agents are given the possibility to communicate, meaning they can exchange information about which exit they are heading towards and their velocity. This could correspond to communication via a mobile phone. To this end they are randomly paired up at the beginning of the simulation and after a set interval t_I, 30 seconds, they start to exchange information. Assume that agent α moves towards the exit S with velocity $v_{\alpha S}$ and its partner β moves towards exit L with velocity $v_{\beta L}$. In this case the utility assigned by agent α to the larger $u_{\alpha L}$ and the smaller $u_{\alpha S}$ exit are

$$u_{\alpha S} = \frac{r_{\alpha S}}{v_{\alpha S}} \quad , \quad u_{\alpha L} = \frac{r_{\alpha L}}{v_{\beta L}} \tag{6}$$

where $r_{\alpha S}$ and $r_{\alpha L}$ are the distance from agent α to the smaller and larger exit respectively. The velocity represents the instantaneous motion towards the target and we use the average motion over the last second of simulation. Communicating agents can revise their decision after the interval t_I has passed.

Smyrnakis and Galla observed that by increasing the fraction of people communicating (cN) the evacuation time decreased until 60% of agents communicate. Any further

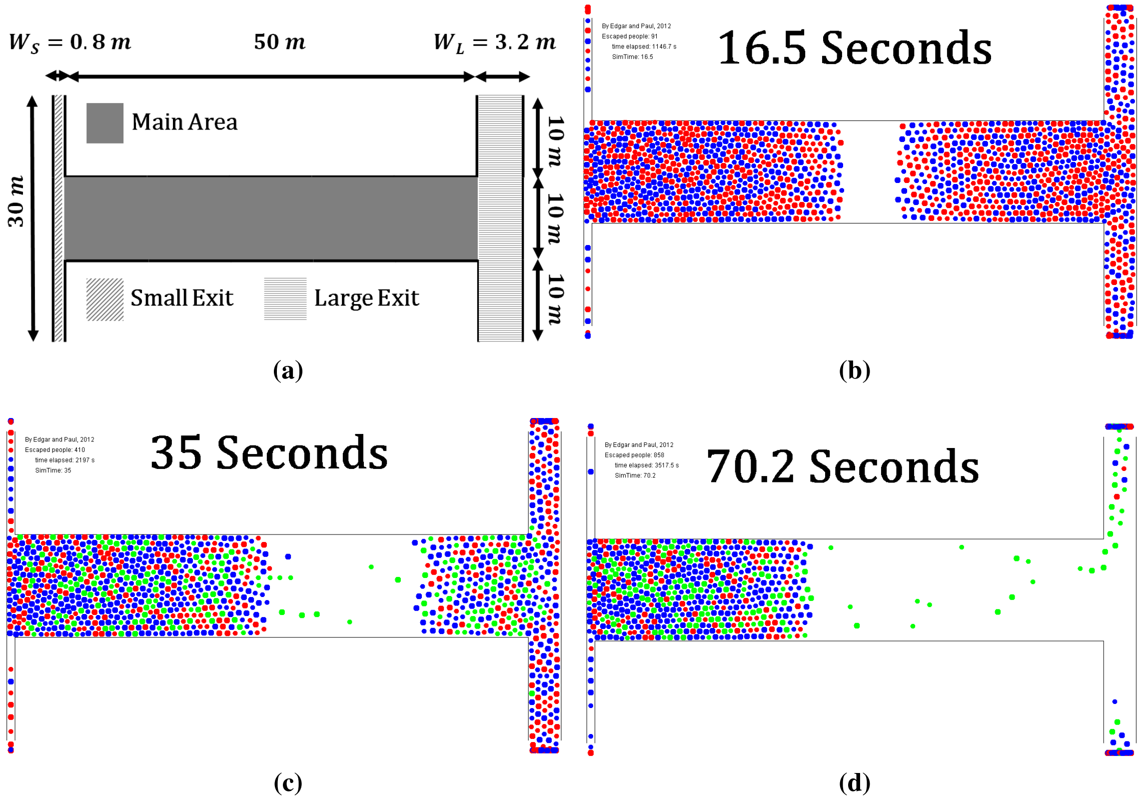
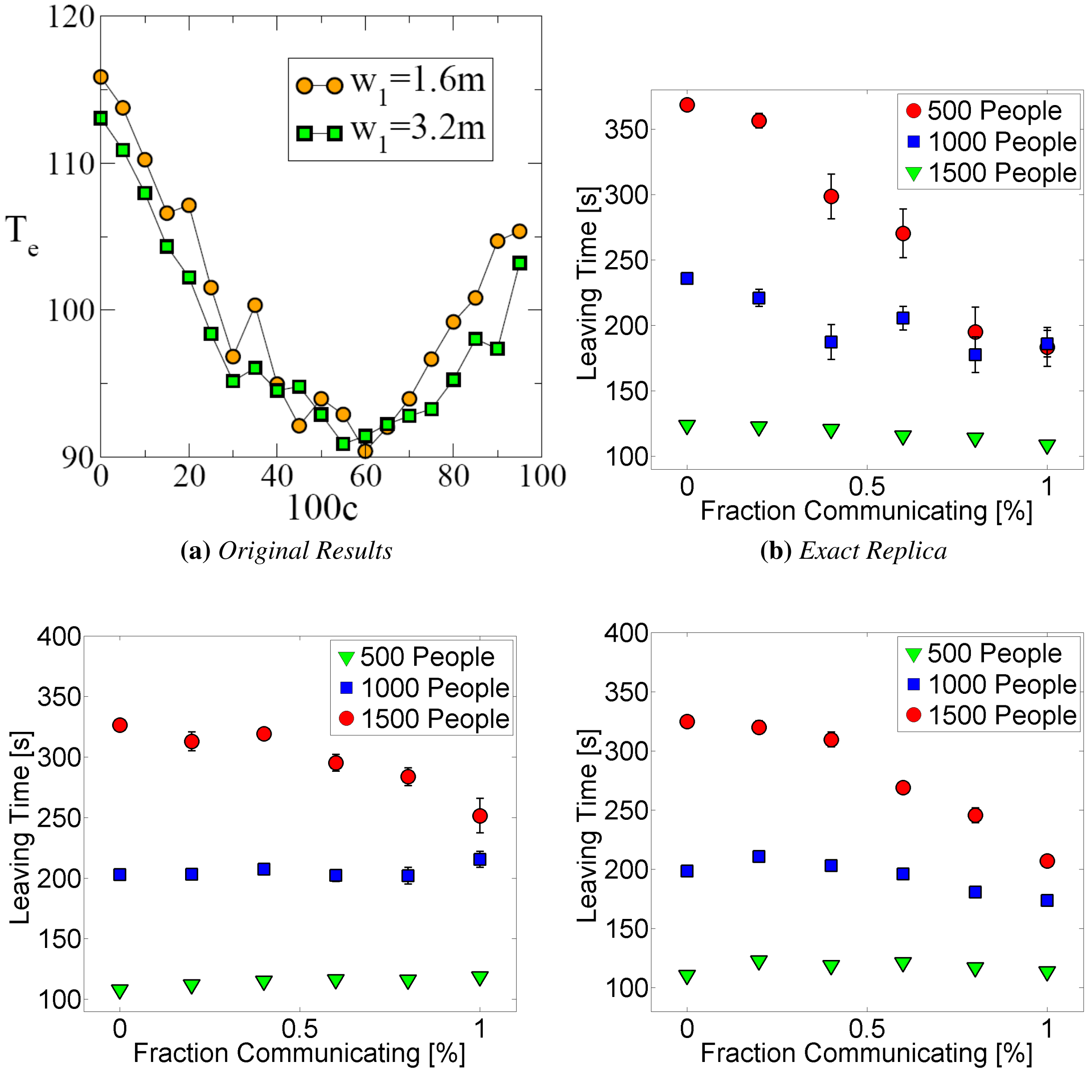


Figure 2: *Schematic of the Bridge Scenario and 3 Screen shots from the simulation at 16.5, 35 and 70.2 seconds with a population of 1500 people with 50% of the population being able to communicate. Pedestrians coloured blue do not have a partner and pedestrians with a partner and therefore able to communicate are coloured red. These turn green when they change their exit.* ***(a)*** *Schematic of the layout.* ***(b)*** *Simulation at 16.5 seconds, all pedestrians are moving towards their closest exit.* ***(c)*** *Simulation at 35 seconds, agents that are able to communicate. The majority of the agents that decided to change exits are trapped in the crowd and cannot move anywhere as the agents behind prevent them from moving* ***(d)*** *The larger exit has emptied and agents that are communicating with a partner that left through the larger exit are trying to move towards it but continue to be blocked by the crowd around them*

increase in communication lead to a increase in evacuation time. Their original graph is show in figure 3(a)

3.2 Reproducing Communication with the Helbing Model

An initial question in reproducing Smyrnakis and Galla communication was what part of their model was due to the discreet nature of the CA and what was a description of the underlying physics. Three distinct set of conditions were used for the simulations. In the first we exactly followed the behaviour of the CA model described by Smyrnakis and Galla. The agents initially move horizontally right or left until they leave the central area and then move towards the closer exit (either up or down). The first modification of this was for the agents to immediately move towards their nearest exit as diagonal motion is possible in the continuous space Helbing model. Lastly, we additionally changed the utility function. Instead of assuming that from the current position an agent could move to



(a) *Original Results* **(b)** *Exact Replica*

(c) *Four Exits* **(d)** *Adapted Utility*

Figure 3: *The effect of phone communication in the bridge scenario. The graphs show the leaving time versus the fraction of the population communicating. The data is averaged over 20 replications and the errorbars are the standard error of the sample.* ***(a)*** *The results of Smyrnakis and Galla using a CA model [8].* ***(b)*** *Exact replication of Smyrnakis and Galla simulation using the Helbing model.* ***(c)*** *In this adaptation the default choice of the pedestrians has been changed so that they move towards the nearest exit immediately instead of moving left/right first.* ***(d)*** *Additionally to changing the default choice as in (c) the utility function has been modified (see (7)).*

the alternative exit at its partners velocity, we introduced a utility function where the agent assumes he can travel at his desired velocity to the other agents position, and from the other agents position at its speed to the exit. Therefore, the utility $u_{\alpha S}$ and $u_{\alpha L}$ assigned by agent α to the smaller and larger exit respectively is given by

$$u_{\alpha S} = \frac{r_{\alpha S}}{v_{\alpha S}} \quad , \quad u_{\alpha L} = \frac{r_{\beta L}}{v_{\beta L}} + \frac{r_{\alpha\beta}}{v^0_\alpha} \tag{7}$$

where the agent β is the partner of agent α as before.

Smyrnakis and Galla used a population of 2100 people for their simulations. For the simulations with the Helbing model, the largest population we used was 1500 people. This corresponds to approximately 85% of the surface of the room being covered by agents. While the number of agents is smaller in our simulations than in those of Smyrnakis and Galla, in our model the agents cover a larger surface area than 2100 people in the CA model, where they cover 67%. Furthermore, the square nature of the cells in the CA model mean it is possible to cover the entire surface area with agents while in the Helbing model this is impossible. The maximal packing of circles in a plane is 90.7 %. As in our simulations agents are placed randomly, this is unlikely to be achieved and therefore 85% is close to the practical maximum.

The leaving times for these three set ups are shown in Figure 3 along with the original results from Smyrnakis and Galla (Figure 3(a)). It is apparent that none of the simulations with the Helbing Model reproduce the originally observed effect.

The exact replica of Smyrnakis and Galla simulation using the Helbing model (Figure 3(b))[2] shows the same initial trend of reducing leaving time with increasing communication. However, in the Helbing model no minima occurs. The CA model predicts much shorter evacuation times with no communication than the Helbing model, 113 seconds for 2100 pedestrians compared to 370 seconds for 1500 pedestrians in the Helbing model. This is due to the ability of the Helbing model to simulate arching and clogging at exits. Two agents trying to enter an exit may block each other moving forward until the pressure from the crowd behind them breaks the symmetry of forces such that one can advance. This can lead to prolonged blockages of the exit unlike in the CA model where one agent always is able to move to a free cell.

The larger the population is the more influence communication has. For a population of 500 people around half will have left the structure by the time agents start communicating and the time to travel to the free, larger exit is almost equivalent to the time until the smaller exits becomes free. For a population of 1000 people communication can slow as well as speed up evacuation times, depending on the initial conditions, i.e. the placement and the pairing of the communicating agents. On average it speed up the evacuation. For 1500 people communication always improves evacuation times.

When the default choice of the agents is changed so that they move towards the closest exit immediately (Figure 3(c)) instead of moving horizontally left/right, the evacuation time with no communication is reduced. At the same time, communication slows down evacuation except for populations of 1500 people. The reason for this slow down is that now, instead of switching between small exits and the larger exits, agents also switch inbetween the larger/smaller exits. When an agents partner escapes through one of the large exits, it is moving fast and the agent decides to switch exits, even if it is already moving to the other large exit. However, as both large exits have an equivalent current this does not lead to a faster exit but creates more gridlock as the agent tries to move against the crowd to the other exit. For large population the benefit of agents switching from one of the smaller exits to one of the larger ones is larger than the slow down created by switches between exits of the same size.

We adapted the utility function that partners would not only exchange exit and velocity but also the position at which they are. The motivation was that an agent crossing the middle of the bridge could actually move uninhibited and the estimation that he would move at his partners speed is an underestimate. Therefore, the new utility function we introduced assumed travel to the partners position at the desired speed v_i^0 of the agent i and the from the partners position to the exit at the partners speed. As shown in figure 3(d), this leads to a steep decline in evacuation time than using Smyrnakis and Galla

[2]Example videos of this and later simulations can be found on http://mphys.herobo.com

original utility function and a smaller dependence on the initial condition, as indicated by the errorbars.

All simulations with the Helbing model show the same general trend, a reduction of evacuation time with increasing communication. The lowest evacuation time occurs when all pedestrians are communicating and this effect is most pronounced for larger populations. However, this does not concur with the findings of Smyrnakis and Galla. While the simulations with the CA model show an improvement in evacuation time with increasing communication, the minima they observed is not reproduced with the Helbing model. The overall larger evacuation time with the Helbing models is most likely due to the more realistic occurrence of gridlock and congestion in this model.

Whether the longer leaving time due to congestion and jams at exits is realistic requires experimental verification which is beyond the scope of this project. However, it seems a valid assumption that there will be some degree of friction and jamming at an exit with large crowds. The discrepancy in evacuation efficiency at high fractions of communicators does not have an apparent explanation. This is a point of further work in our second semester. The general results of Smranski and Galla, that communication between agents speeds up evacuation time, holds true with the Helbing model.

The effect of desired velocity has not been investigated to date, mainly because of a lack of computing power. In the CA model the velocity is determined by what time is associated with each step and hence is a scale factor. In the Helbing model, the desired velocity has a large effect on the behaviour of the system, as is show by the faster-is-slower effect observed in evacuation from a room (see section 2.2). This will be our starting point in the second semester.

3.3 "Text Messaging" Communication

We had two motivations for introducing an alternative form of communication. The drawback of the abstraction of the Smyrnakis and Galla model is that there is no one-to-one translation to real evacuation situation. Groups and people that know each other generally stay together and pedestrians display herding behaviour [10]. It is therefore unlikely for a large fraction of pedestrians in a given evacuation to be able to communicate with a partner in a different exit. Additionally, we were interested in a model that allows us to influence the number of pedestrians going to each exit more directly.

To this end we introduced what we term the "Text messaging" model. A fraction of the population, randomly selected, is presented with the instructions that to go to one of the two large exits. If the agent in question is already using this exit then this does not change its motion. Likewise, if the agent has left through one of the exits already, it does not revise its choice. We use the continuous-space version of the non-communicating utility function i.e. the agents move towards the closest out of the four exits as our default choice rather than moving horizontally right or left initially.

In reality pedestrians would have a certain propensity to follow an instruction from e.g. a text message sent by a central system. However, as this just scales the overall number of people following external advice we did not include a probabilistic propensity in our model. This would introduce a further stochastic variable and the model already has a stochastic element in it as the initial position of pedestrians is randomly assigned. This introduces the constrain on our results at large percentages of "texted" people will not be reproducible in real live. The actual propensity to follow is an experimental constant to be determined. In the meantime, this model allows the investigation of the effect of a central

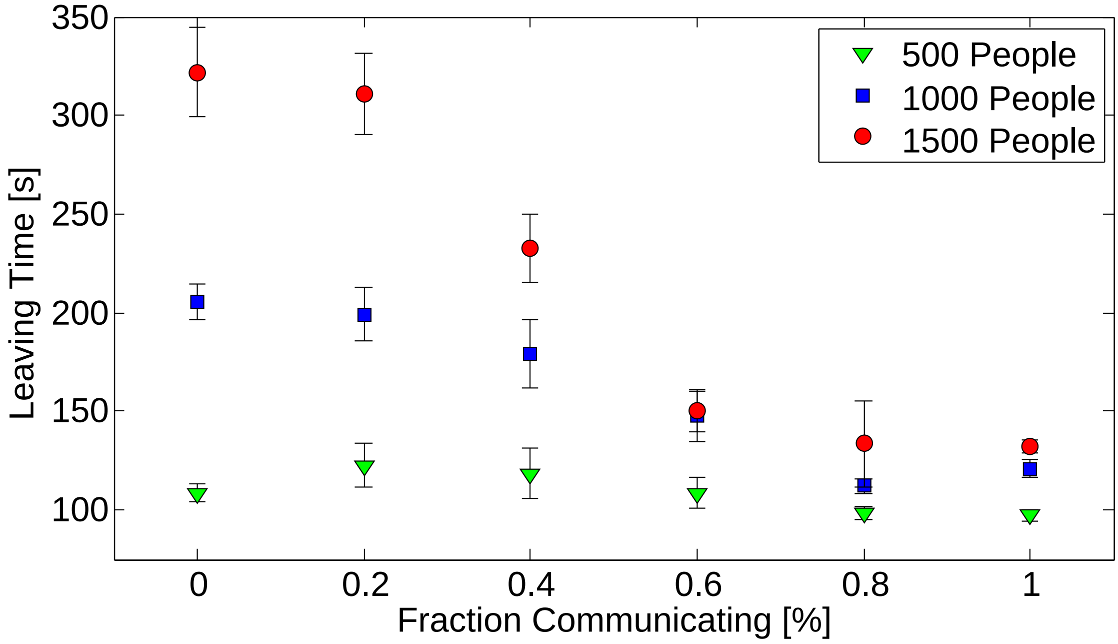


Figure 4: *The effect of communication by a central authority in the bridge scenario. The graphs show the leaving time versus the fraction of the population being directed towards the larger exits. The data is averaged over 20 replication and the errorbars are the standard deviation of the sample, the standard error being of the size of the data points.*

directing agent on evacuation flow.

The results are shown in Figure 4. It should be noted that the errorbars in this graph indicate the standard deviation of the sample as the standard errors were of the size of data points. As for the reproduction of the Smyrnakis and Galla model we restricted ourselves to populations size of up to 1500 people. For large enough populations, directing the agents always leads to an improvement in evacuation time. The slight rise in evacuation time observed for a population of 500 people is caused by the slow-down due to counter flowing pedestrians. The agents that receive the information to change exit turn around and are blocked by the agents behind them. This keeps them trapped until the agents behind have flown around them. By this point, the time it takes the pedestrians to travel to the larger exit is larger than the time it would take them to escape through the smaller exit, leading to an increase in evacuation time.

It is notable that for the fraction communicating $cN \geq 0.6$ the evacuation time is around 150 seconds independent of the population size. This stems from the inefficient default choice of a quarter of the population going through each exit even though the larger exits have a fourfold larger capacity than the smaller ones. To a certain extent it is not surprising that distributing pedestrians among exits according to the exits capacity leads to an improvement over an equal allocation of pedestrians to each. However, this is in accordance with observed evacuation behaviour where pedestrians tend to us the door they used to enter the structure to exit, even if closer exits are available.

This method of communication shows the largest decrease in evacuation time, 50% for a population of 1500 people. As for the ”phone” communication scenario proposed by Smyranski and Galla, the effect of desired velocity remains to be investigated.

4 The Corridor Scenario

We implemented this scenario because it is a natural test of computer simulations as well as a further comparison between CA models and the Helbing model. A recent paper using a floor field CA by Schadschneider and Nowak [9] has served as a point of comparison, allowing us to continue the investigation of the differences between CA models and the Helbing Model. My partner Paul Vriend wrote the code and collected the data for this scenario. However, we consulted each other continuously on our projects and solved any problem that appeared together.

Spontaneous segregation is observed in several physical systems such as colloidal suspensions [12] or granular materials [13] . From everyday experience it is best know through pedestrian counterflow where pedestrians have different walking directions. This has been observed experimentally (e.g. [14]) and is a common qualitative test of computer simulations. However, there are few quantitative descriptions of lane formation. A focus of the study of bidirectional flow is the transition to gridlock, where no movement is possible. These appear in models but have not been observed experimentally. A lower density limit for this transition to occur has be given as $3.5P/m^2$ by Zhang *et al* [15]. In our simulation we do not have pedestrian densities over $3P/m^2$ and therefore any occurrence of gridlock is unrealistic. However, as pedestrians can "squeeze" past each other, which the spherical particles in our model cannot, the occurrence of gridlock is to be expected in our model.

4.1 Set Up

Our initial approach was to create a corridor of a set length and inject particles at either end. When these particles reached the opposing end of the corridor they were removed. This lead to a large number of problems, such as instability, as the injection of particles disturbed the flow. As a result we implemented periodic boundary conditions, i.e. a particle that leaves the corridor at one end, enters at the other. At the beginning of each simulation we randomly distributed the pedestrians over the available area. This resolved all problems and made it possible to have a clearly defined density of pedestrians. Pedestrians of type A (coloured blue) wish to move towards the right while pedestrians of type B (coloured red) move towards the left.

4.2 Definition of Different States

The patters observed in a corridor with counter flowing streams of pedestrians can be characterised by four states, illustrated in figure 5. For low particle densities where the average distances between particles is too large for any interaction to occur, the system is said to be in free flow. As the density increases a state of disorder occurs where particles interact but not enough for any emergent phenomena to appear. Lane formation occurs at equivalent and higher densities where particles are in close contact. Eventually, gridlock develops, the jamming of the complete system such that no movement in the desired direction is possible.

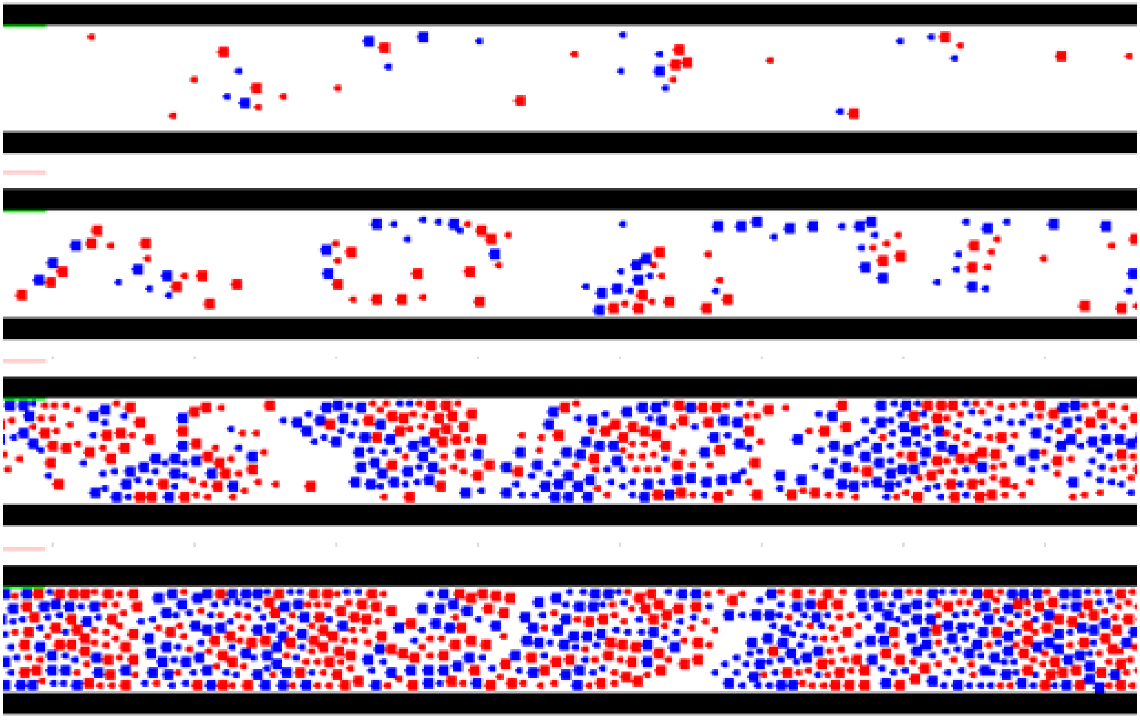


Figure 5: *Illustration of the four phases of pedestrian motion in a corridor. From the top to bottom free flow, disorder, lane formation and gridlock are shown. Blue particles wish to move towards the right while red particles move towards the left.*

4.3 Order Parameters

As lane formation is often used to validate a model we found it surprising that there are few attempts that go beyond the observation that lanes are present in a system. Our first aim was to find a systematic way to classify lane formation. The difficulty becomes apparent when one investigates a picture, such as the bottom corridor in figure 5, as lane formation is a dynamic phenomena. One possible parameter has been introduced by Schadschneider and Nowak [9]. This order parameter together with the density can distinguish between the four states of free flow, disorder, lanes and gridlock in the CA model. However, we found that this was not adequate for the Helbing model: situations which we visually judged to contain a large number of lanes had lower order parameters than those we judge to be in disorder.

This stems largely from the difference between the CA model and the Helbing model. While in the CA models, particles move in straight lines unless blocked , in the Helbing model, motion generally is of diagonal nature due to the many forces acting on the pedestrians. As a result, the definition of an order parameter is more complex. As Schadschneider *et al* used the order parameter for the classification of the states of the system, our starting point was to find an order parameter that works with continues space models.

4.3.1 Schadschneider and Nowak Order Parameter

Based on a paper by Nowak and Schadschneider [9] this order parameter is inspired by a parameter used to detect lanes in colloidal suspensions. This parameters counts the number of pedestrians with the same N^A and opposite N^B direction in the lane for each pedestrian. As Schadschneider and Nowak use a floor field CA, they only consider the row the particle is in. More generally one includes particles whos lateral distance, i.e. the distance perpendicular to the direction of the motion, is below a certain threshold x_0 (we took x_0 to be 1.5 times the radius). For each particle n the order parameter ϕ_n is given by

$$\phi_n = \left(\frac{N_{i_n}^A - N_{i_n}^B}{N_{i_n}^A + N_{i_n}^B} \right)^2 \tag{8}$$

where i_n is the row of particle n and N_i^A (N_i^B) denotes the number of type A (B) at row i. The order parameter for the complete system is then give by the means

$$\Phi = \frac{1}{N} \sum_{n=1}^{N} \phi_n \tag{9}$$

where N is the total population. The value of Φ is in general larger than zero even if all particles are distributed at random. The mean value of Φ with a random distribution is denoted by Φ_0 and for small densities Φ_0 can be large even though there is not lane structure in the system. This is taken into account by defining a reduced order parameter $\tilde{\Phi}$

$$\tilde{\Phi} = \frac{\Phi - \Phi_0}{1 - \Phi_0} \tag{10}$$

which can be less than zero. We introduced a horizon for this parameter to account for lane formation being local. A horizon of 10 particle lengths was introduced to account for the more dynamic nature of the simulations with the Helbing model.

4.3.2 Nearest Neighbour Order Parameter

The nearest neighbour order parameter (NN OP) was motivated by the idea that the dynamics can be described by the local environment. For this parameter, for each pedestrian we find the nearest neighbour. If it is travelling in the same direction, then we add one to the overall order parameter, if it is moving in the opposite direction, we subtract one. The overall order parameter is divided by the population N and is in the range [-1,1]. For convenience we scaled it such that it lies in the range [0, 1] where zero indicates perfect mixing and 1 indicates that all pedestrians are moving in the same direction as their nearest neighbour.

4.3.3 Correlation Order Parameter

The correlation order parameter (C-OP) correlates the direction of motion of the particle with the direction of motion of its nearest particle. Only particles within twice the average inter-particle distance are considered as for large distances no interactions can occur between them. The average inter-particle distance is the distance between particles if they are evenly distributed in the available area.

If the direction of motion of a particle is within $45°$ of that of its nearest neighbour, we added one to the overall order parameter. After this has been done for the whole population N, the overall order parameter is divided by N, giving a value in the range [0,1] where large values correspond to larger correlation between the velocity of the pedestrians.

4.3.4 H-index Order Parameter

The h-index was proposed by Hirsch as a tool for determining both the productivity and impact of the published work of theoretical physicists. It is defined as [16]:

> A scientist has an index h if h of his N_p papers have at least h citations each, and the other $(N_p - h)$ papers have no more than h citations each.

Adapting this definition to pedestrian motion, we consider each particle and count the number of particles within its horizon that are moving in the same direction and subtract the number of particles that are moving in the opposite direction. The horizon is defined analogous to the horizon for the Schadschneider parameter. The h index for the entire system then is the number of particles that have an h-index of h or greater.

4.4 Comparison of Order Parameters

The value of the order parameters is plotted against the pedestrian density in the corridor in figure 6. We observed the lane formation generally occurs in the density region $0.35 < \rho_{lane} < 1.5\ P/m^2$. A parameter that would indicate lane formation consistently would have a range of values in this region, depending whether the specific simulation exhibits lane formation, allowing us to distinguish between disorder and lane formation.

Neither the Schadschneider nor the Schadschneider reduced order parameter allows lanes to be distinguished. This is because most lanes observed with the Helbing model have a diagonal component and hence do not contribute to the Schadschneider order parameter which measures lanes only along the horizontal axis. The h-index initially reflects the increasing density and at high density reflects how tightly the pedestrians are clustered. However, it does not show the presence of lanes.

The nearest neighbour (NN) and the correlated order parameter are independent of density and show fluctuations over the region of interest. Upon closer examination of simulations, the correlated order parameter was found not to correspond to lane formation while the NN order parameter did correspond partial. Here partial means that for certain simulation runs, the NN order parameter did indeed correspond to the degree of lane formation observed. However, in a significant fraction of the simulations the order parameter did not correspond to the degree of lane formation. As we judged the degree of lane formation on a subjective scale, these observations are not presented in detail here. We felt that none of the order parameters correlated closely enough with the observed degree of lane formation to warrant a more systematic investigation.

We concluded that there is not simple method apparent to use that can quantify the degree of lane formation in the Helbing model. In the light of this observation it is not surprising that there have been few attempts at quantifying the lane formation in experimental data or computer simulation.

5 The T-Junction Scenario

This scenario is based on a paper of Galla [17]: people encounter a junction with two, asymmetric exits. The effect of a dynamical sign on the total current is investigated. There are the results from a simulation with a cellular automaton model as well as analytic solutions. We have implemented this scenario, a screen shot is shown in Figure 7 (with

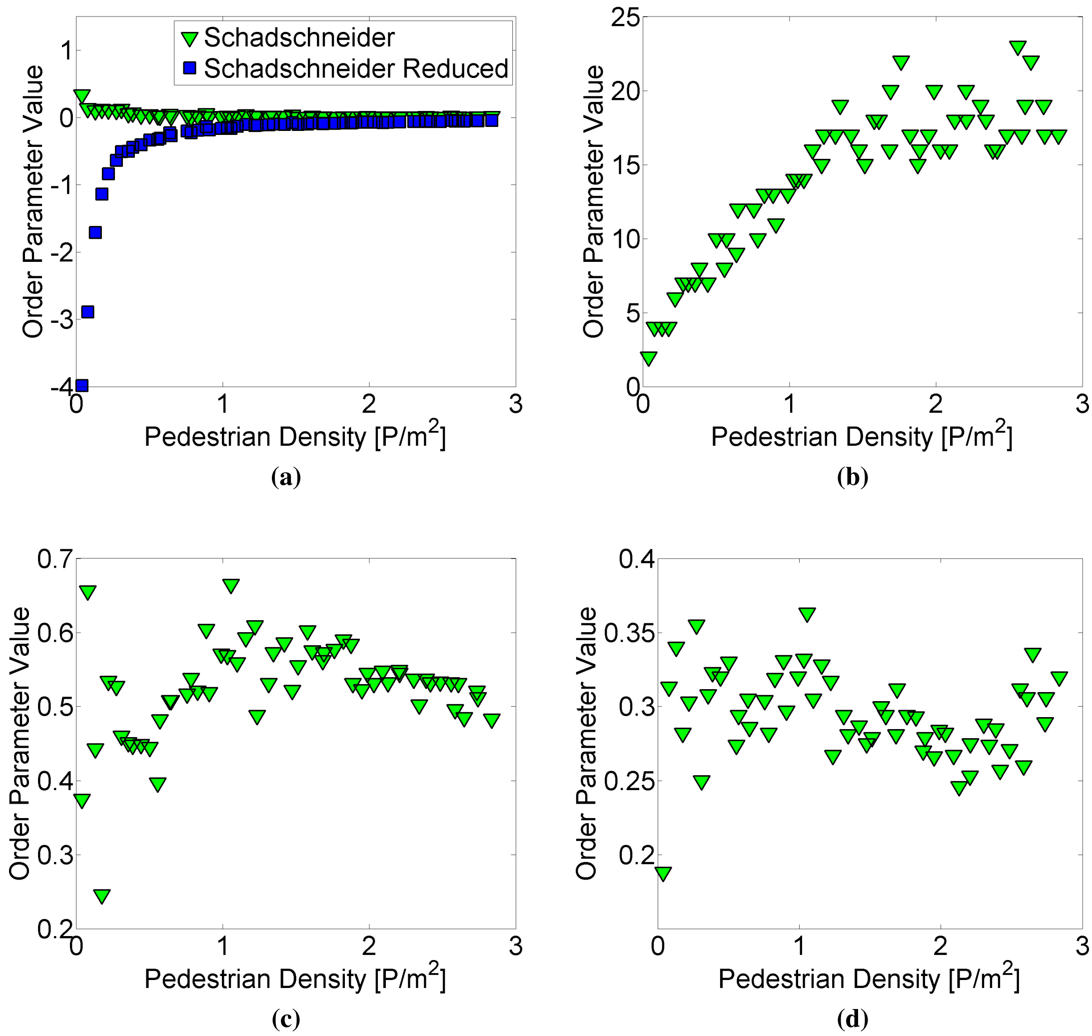


Figure 6: *The five order parameters investigated against pedestrian density in corridor.* ***(a)*** *Schadschneider and Schadschneider Reduced Order Parameter* ***(b)*** *h-index Order Parameter* ***(c)*** *Nearest Neighbour Order Parameter* ***(d)*** *Correlated Order Parameter*

symmetric exits), but did not have the time to systematically investigate it. In the 2nd Semester we hope to use it as it allows a good comparison of cellular automaton and social forces model against the base line of the analytic solution.

6 Summary and Outlook

We have investigated the differences between reductionist CA models and the more detailed approach of the Helbing model. In the case of evacuations from a large structure (the "Bridge" scenario) we have confirmed the observation that communication improves evacuation times for large pedestrian densities. However, the observation that there is a minima of evacuation time at 60% of the population communicating has not been reproduced. The evacuation times in the Helbing model are larger than in the CA model but this is expected as the size of the agents is larger in the Helbing model and the Helbing model can produce gridlock and clogging at exits. A new form of communication

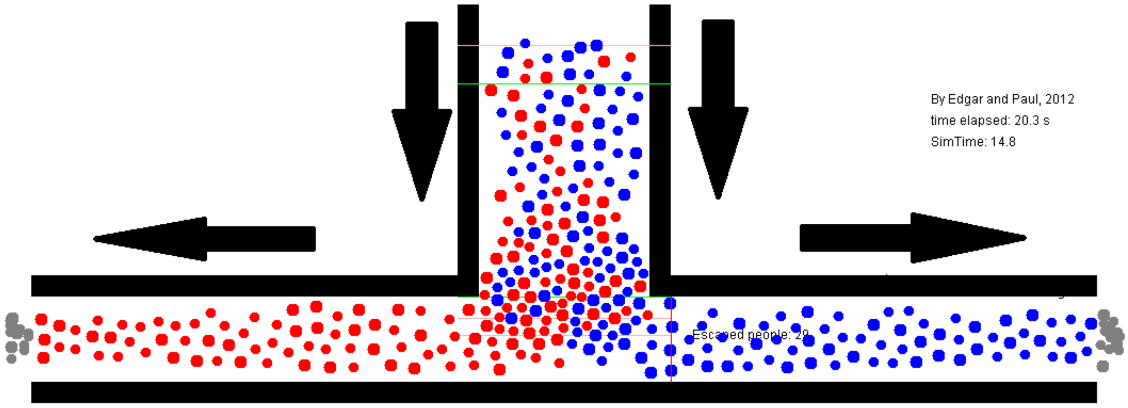


Figure 7: *Layout of T-Junction scenario. The arrows indicate the direction of motion. When the pedestrians are created, they have a randomly determined target at the wall of the T-Junction. Pedestrians that have targets on the left are coloured red while those with targets on the right are coloured blue. When they move into the junction, they move left/right depending which exit is closer.*

was introduced by us, where we showed that a directing agent allows for a more efficient evacuation.

The measurements for the Bridge scenario have been performed at a pedestrian desired velocity of $1.2m/s$. Our further work will focus on investigating these effects at different velocities.

In the ”corridor” scenario we have tried to find a parameter that allows us to quantify the degree of lane formation in a system. The adaptation of the order parameter from the spatially discreet CA model failed to identify lane formation as well as the other order parameters we created. It remains an open question what an effective measure of lane formation is in a spatially continuous system.

We implemented a T-Junction as previous work have both solved this scenario analytically as well as investigated with simulations with a CA model. In the second semester this would be a promising point for evaluating the difference between the Helbing and CA model that we discovered against the baseline of the analytic solution.

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