UNIVERSIDAD DE LAS AMÉRICAS PUEBLA

ESCUELA DE CIENCIAS

DEPARTAMENTO DE ACTUARÍA, FÍSICA Y MATEMÁTICAS

IMPACT OF GROUP SENSITIVITY PARAMETERS IN A CELLULAR AUTOMATA MODEL FOR PEDESTRIAN EVACUATION PROCESSES

TRABAJO DE INVESTIGACIÓN QUE PRESENTA LA ESTUDIANTE

SILVIA ANDREA MORALES MANZANO

159068

DIRECTOR: DR. MIGUEL ÁNGEL OCAÑA BRIBIESCA

SAN ANDRÉS CHOLULA, PUEBLA. OTOÑO 2022

Contact Details

GitHub: `https://github.com/Silvia-exe/`

Institutional Email: `silvia.moralesmo@udlap.mx`

Personal Email: `silmor1999@gmail.com`

Trabajo de investigación que presenta la estudiante Silvia Andrea Morales Manzano, 159068

Asesor del proyecto

Dr. Miguel Ángel Ocaña Bribiesca

Nombre del Director

Presidente de Tesis

Dra. Milagros Zeballos Rebaza

Nombre del Presidente

Secretario de Tesis

Dr. Noureddine Lakouari

Nombre del Secretario

Contents

Abstract

A new floor field cellular automaton model for pedestrian evacuation dynamics is presented. This model, based on Kirchner et al. FFCA (2002), adds heterogenous pedestrian population by dividing the initial pedestrian population of a room into two groups with different sensitivity parameters to the static and dynamic floor field. The inspiration of this model comes from the fact that pedestrians will follow a general zone of high flow, but there will be several individuals who will be more aware of their surrounding than others. This thesis' implementation of heterogeneous pedestrian population focuses on two pedestrian groups following the same global dynamic and static floor fields albeit coupled to them with different sensitivity parameter pairs. The group's sensitivity parameters are based on the evacuation regimes, Ordered, Disordered, and Optimal. We evaluate the average of the evacuation times of a 63×63 cells room with initial group configurations in order to study the evacuation process of different pedestrian populations by the means of the sensitivity parameters. It is concluded that groups with higher values of $k_{\mathcal{D}i}$ will not add useful information to an evacuation dynamic by being more prone to follow the regions of higher flow, but will slow average evacuation processes. Finally, a new work flow is proposed, in which further contributions to the field of pedestrian dynamics is ought to be open-source and documented.

Key Words: Pedestrian Dynamics, Cellular Automata, Floor Fields.

1 Introduction

With high-end computers being more and more accessible, computational researchers have taken interest in the study and modelling of biological phenomena using an interdisciplinary approach that searches for analogies between physical and biological systems and vice versa [1]. This interdisciplinary emerging branch of science aims to explain complex biological systems with the usage of physical laws.

One such complex biological system is the behavior of a large group of people, a crowd. Crowd dynamics or pedestrian dynamics is a study that aims to explain and predict emergent phenomena which arises in dense, packed groups of people [1] [2]. Further interest aroused in pedestrian modelling since empirical observations and research has shown that masses of pedestrians will showcase spontaneous and emergent organized behaviors such as oscillations, lane forming, trail forming and jamming [3][1][4]. These brief clusters of organization emerging from a seemingly chaotic system of non-cooperative pedestrians (meaning, seemingly no communication between individuals) encourage the idea of the system having self-organizing properties such as a thermodynamic system undergoing phase transitions.

Laws and models which simulate pedestrian dynamics are still being researched and there is no one general model yet to be accepted by academic research as the best modelling approach. It is noted that the study of pedestrian dynamics is of great importance in the field of civil engineering, since this allows us to understand the behavior of a crowd in emergency situations, for example an evacuation [2]. This in turn will diminish evacuation times and increase the uninterrupted flow of pedestrians which will relate to a lower amount of injury and casualties [1].

One such model is the Floor Field Cellular Automata Model, proposed by the work of Angsar Kirchner and Andreas Schadschneider [4]. This thesis will firstly aim to replicate Kirchner et al. results with a new open-source coded implementation. Afterwards, we present this thesis' model proposal for the Group Sensitivity Parameters Floor Field Cellular Automata model (GSP FFCA). It bases itself on introducing new sensitivity parameters for a heterogeneous group of pedestrians. This aims to create a more realistic model simulation of pedestrians. Moreover, several group definitions and initial population configurations will be studied and presented as representations of different real-life scenarios.

This work also aims to make the research of pedestrian dynamics an open source and collaborative field. Since simulations vary significantly dependant on small tweaks in algorithms, it is of most importance to note down the variations done and results gotten from different implementation. In order to achieve this, an open-source repository

[1]Scientific aim of finding inspiration in nature to model physical systems is known as bionics.

will be discussed as a new approach in research.

We will briefly discuss the phenomena of pedestrian dynamics, and the different proposed models for their simulation. Then, we will focus on the motivation for cellular automata based models. Afterwards, we will present our new proposed model which redefines the original sensitivity parameters proposed by Kirchner et al. model [4]. Additionally we will present the qualitative and quantitative qualities and behaviors of the GSP FFCA model proposed in this thesis. Finally, we will present new lines of future work that may include proposals for new, more detailed models.

2 Simulation of Pedestrian Dynamics

Highly populated cities are more prevalent now than ever, with 56% of the global population living in urban areas [5]. Thus, dense automobile traffic is now a common occurrence in day to day urban transit, coexisting with high density pedestrian crowds. The optimization of traffic to reduce commuting time and gas emissions has become a priority in city design. Traffic has state variables, such as flow and average speed, which are affected by street design for example. Traffic dynamics, or the behavior of vehicular traffic in different scenarios has been studied intensely by the usage of physics-based models. Preliminary studies started as a purely empirical branch, born out of a mere observation of one dimensional traffic flow, which was in the form of one-way automobile traffic [6]. Furthermore, this one-dimensional system has been modelled extensively by the usage of analytical approaches which have computationally replicated phenomena seen in real life situations. One such traffic-modelling theories are the Fluid-dynamical theories of vehicular traffic. These base themselves of modelling the traffic as a compressible fluid, and state variables such as flux and local density are calculated by the use of differential equations. By using physical bases such as the Navier-Stokes equations, phenomena such as spontaneous traffic jams have been modelled [7] ([8] for a review on traffic dynamics). Pedestrian dynamics, which is the study of the behavior of a large mass of people, has not been studied as thoroughly. This is an emerging field of study which has caught the interest of researchers since this seemingly chaotic and complex arrangement showcases emerging collective effects which can be compared to well-studied physical systems. In the same nature, dense crowd flows transiting through a city are now a common occurrence. In such densely populated cities, closed areas populated with high density of visitors and massive events are regular. This creates now the need to study the behavior of dense crowds in an enclosed area in order to be able to manage pedestrian traffic, and this need is exacerbated when emergency situations force an evacuation process of these masses of people. There is now the need to create efficient and fast evacuation processes in order to minimize risk of injury.

Pedestrian dynamics is born out of the need to understand the emergent phenomena of masses of people and their general behaviors such as flow speed. An example of empirical dynamics unique for a crowd system is the creation of blockages, line formation, oscillations and trampling from bottle-neck jams. The models proposed for pedestrian modelling must showcase these complex, emergent behaviors. This is more complicated than for one-dimensional vehicular traffic since a group of pedestrians are inherently a 2-dimensional system. This fact adds new degrees of freedom to the one-dimensional traffic models. Since real-time, empirical experiments of pedestrian dynamics are difficult to set up and measure, excluding the fact that emergency evacuation processes might be impossible to fully recreate, research has focused on creating computationally efficient, simple models but, which, in their simplicity, do not stray away from simulating real life scenarios [4][9]. As a particle system, pedestrian dynamics will act as a statistic and thermodynamical system. Pedestrian-particles are affected by forces of repulsion and attraction, for example, attraction to a show scenario, a shopping window or an exit. It is also noted that forces of attraction may be felt between pedestrians, such as the natural attraction to high-flow areas to simplify the individual's own movement, or when there is a couple walking (mother-child for example), affecting the path taken. Repulsion forces to unknown pedestrians, and to walls for example, also affect the route walked. The effect of these forces depend on the arising situation, in which, for example in the case of a high-stress scenario, forces of repulsion to strangers are weaker since emergency situations will diminish the necessity of personal space [9]. Pedestrian particle systems have state variables which allow us to describe the system, such as density, volume and average speed [10]. Moreover, simulations of pedestrians in evacuation processes are focused on modelling evacuation times for different geometries and configurations, for example. In order to research the evolution of a pedestrian dynamic evacuation process and thus optimize it, several physical-computational models have been proposed.

2.1 Proposed Models

The proposed models fall into one of two categories; macroscopic and microscopic. A macroscopic model bases itself on describing the evolution of one of the chosen state variables through time. This model supposes all particles to be identical and indistinguishable, such as in a monotonic gas. One example of a model based on this approach is that of the hydrodynamic model, in which traffic is seen as a compressible fluid [2]. The Navier-Stokes pedestrian flow models pedestrians as a fluid and thus there is no differentiation between particles. The state variables such as viscosity, speed and density are simulated with differential equations and numerical methods ([10], [11], [12]).

Microscopic models focus on simulating several pedestrian-particles individually, with different forces or rules affecting their individual movements. The behavior of each individual pedestrian is simulated, and one can differentiate between entities. From these individual interactions we expect emerging behaviors which will be visible on a macroscopical scale. State variables could be measured from this model, but since we are modeling individual interactions, particles (In this thesis pedestrian and particle will be used as interchangeable terms) are completely distinguishable [4]. The particle's variables will be affected by its surroundings, but will not follow the same behavior as a physical particle. A consideration we have to take, for example, is the violation of Newton's Third law, since pedestrians are propelled by inner forces and might stop and go at will.

In literature, we can find examples of several microscopic models which allow us to characterize individual pedestrians as particles ([13], [14], [15]). One notorious example of such models, which has shown promising results such as the expected emergent behaviors is the Social Force model. This model applies a repulsive or attractive force upon each pedestrian. This force is exerted by other pedestrians and by the geometry of the room, simulating the acceleration and deceleration of a pedestrian due to external input. The Social Force model is continuous in nature since the velocity, position and acceleration of each pedestrian is given by vectorial quantities calculated with simple differential equations. This repulsive social force between pedestrians decays exponentially to the distance between them ([16], [17]). These relations are akin to coupled equations of motion and thus, for a simulation of N pedestrians, the order of magnitude of interactions calculated each step of the simulation is $\mathcal{O}(N^2)$. This ignores the fact that complex geometries may cause conflicts between pedestrians, since particles could be geometrically close, but separated by an obstacle such as a wall. This forces the simulation to also check if interactions are possible. This results in a time-consuming operation which creates the need of a new model that can reduce the calculation time by reducing the range of interactions with pedestrians

In order to reduce the computational burden, a new discrete model was proposed [4]. This model allows pedestrians only to interact with their immediate neighbors, thus one single interaction per pedestrian has to be computed. This results in $\mathcal{O}(N)$ interactions. The discrete nature of the model also allows for an easy and modular implementation, ideal for Object-Oriented programming. This microscopic, discrete model is based on cellular automata and bears the name of Floor Field Cellular Automata [4] [18].

3 Floor Field Cellular Automata Pedestrian Model

The Floor Field Cellular Automata model for pedestrians (FFCA model) was introduced by Schadschneider and Kirchner in [4] as an alternative to the Social Force model [16] [17]. It is a two dimensional model of pedestrians in which the update rules are based upon the idea of cellular automata. This model is shown to replicate emergent phenomena while also lowering the computational burden by diminishing interactions between pedestrians. One strong advantage is the relatively easy implementation compared to other models. It is also extremely modular and benefits from an Object Oriented focus, which allows us to add modifications to it with ease.

3.1 Generalities of Cellular Automata

Cellular automata are a physical, mathematical and computational tool defined, in their simplest form, as a one-dimensional lattice of discrete sites (cells) which can hold the values one or zero. A more general definition could be created by a three (or n) dimensional discrete lattice of spaces, which can hold one of any m discrete values [19]. The lattice's structure could be made of hexagonal or irregular cells, but simple, general models usually base themselves on a square regular lattice. At each time step, the value of the cell is changed by a set of updating rules which are dependent only on the state of their immediate neighbors. This is done synchronously, so each cell is updated at the same time.

One famous example of applied cellular automata is Conway's Game of Life [20]. In classic Conway's Life, a two dimensional, uniformly gridded, cellular automaton is designed. The cells can hold two possible values, 0 (dead) and 1 (alive). The model has very simple update rules, based on the cells immediate neighbors which are defined as in Figure 1. The update rules are as follows:

1. If an alive cell (value 1) is surrounded by less than 2 alive (value 1) neighbors, the cell dies (becomes value 0) due to "loneliness".
2. An alive cell (value 1) with more than 4 alive (value 1) neighbors dies (becomes value 0) due to "overpopulation".
3. A cell surrounded by two or three alive neighbors (value 1) survives (keeps value 1).
4. A "dead" cell (value 0) surrounded by 3 alive neighbors becomes alive (becomes value 1).

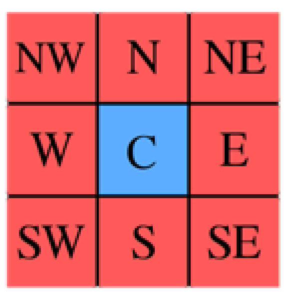
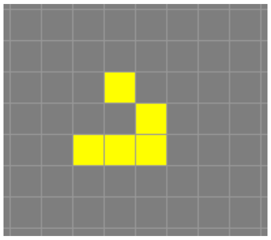


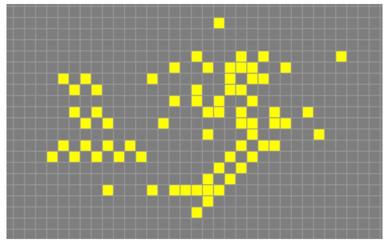
Figure 1: The red cells show the neighborhood of the blue cell. This neighborhood is defined as the Moore neighborhood of a cell [21].

These four simple rules create a single player game where significant complex emergence is apparent. Self-replicating structures, sliding "spaceships" and spinning columns are examples of such behavior [2]. This simple example opens the possibility of being able to explain complex, seemingly chaotic systems as a simple collection of rules being

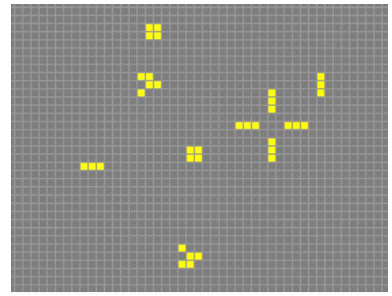
[2] Game can be played online at https://playgameoflife.com/info



(a) Most known Game of Life structure known as a glider. This structure will autopropel itself diagonally. In Game of Life (GoL) lingo, this is also known as a ”spaceship”.



(b) Random initial condition for a GoL evolution. From here on, cells will evolve according to the specified rules.



(c) Evolution of the initial conditions. Several gliders have been created. The system will continue to evolve until all cells die or find a stable equilibrium. This could take several thousand iterations.

Figure 2: Screenshots of different behaviors found in Conway’s Game of Life

followed by discrete, simple structures. Some structures are showcased in Figure 2.

The evolution of any cellular automata will be given by the rules defined for it. It is noted that any small variation in these rules and or in the initial conditions will cause a dramatic change in the evolution of the system, so such a system is known to be chaotic, complex and highly dependent on initial conditions, but explained by simple update rules. The rules imposed on the system can also be defined in such a way that they now act as interacting forces between the cells. The interest in microscopic models such as this, is the emerging behaviors observed. By setting up microscopic interacting forces as update rules which each cell will follow, we can now observe the emergence and evolution of macroscopic properties. This approach allows us to model individual pedestrian-pedestrian and pedestrian-environment interactions by a set of rules.

3.2 Basic Principles of the Model

Computational models of large crowds of thousands of entities require lightweight, simple models that can also replicate real-life scenarios and phenomena. Kirchner. et al. (2002) proposes a cellular automata based model where pedestrians will move according to a set of transition probabilities which are calculated by the values and states of their neighbors [4]. This simplification of the model ignores complex human behavior or any type of intelligence, since the pedestrian’s movement is based only upon quick, almost automatic decisions made only from information from their immediate surroundings.

The proposed model is based on a 2-dimensional space, divided into uniform cells making a square finite grid. This discrete space will be referred also as the movement matrix. Each of the cells of the matrix have two possible states:

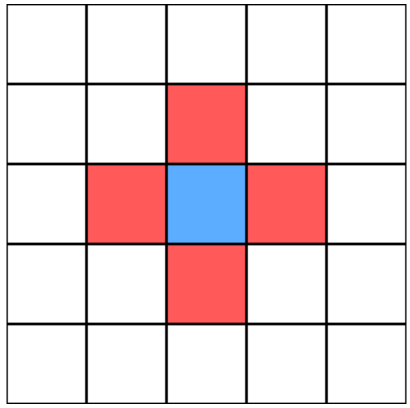


Figure 3: The basic von Neumann neighborhood of the blue cell is defined as the red cells.

occupied (by a pedestrian, walls or obstacle) or unoccupied. The status of the cells is updated every time step based on the pedestrians' movements. The pedestrians are affected by an exclusion principle; a cell can be inhabited by one and only one pedestrian. The exclusion principle is to model a repulsive social force, which we subconsciously follow in order to not bump into someone. This results in a cell being equivalent to a 40 cm $\times$ 40 cm square in which the pedestrian stands. Pedestrians can take one step every update, and this update is done in parallel, which means that all pedestrians take a step at the same time. This time-step is a rough simulation of human reaction time, approximately 0.3 seconds [22] [3].

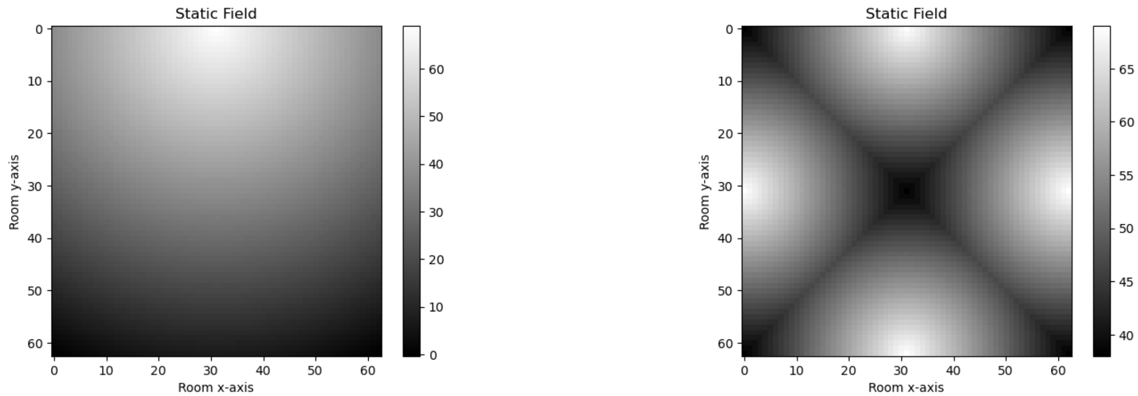
Each pedestrian is given a neighborhood defined by its immediate neighbors excluding diagonals known as the von Neumman neighborhood, as shown in figure 3. Thus, a pedestrian has five movement possibilities; north, west, east, south and center. The pedestrians are not hard-coded with a preferred movement, which is the case of models with the addition of a preference matrix [18], thus the transition probabilities are dependent only on the state of the neighboring cells. It is important to note that the only direct interaction between pedestrians is the exclusion principle, and no direct communication exists between them, there is no bonding between particles.

3.3 Definition of Floor Fields

In order to model pedestrian movements, we have to define their interaction to the geometry of the room and interactions with other pedestrians. To model the interactions the pedestrians have with their environment and with other pedestrians whilst ignoring long distance interactions, the concept of floor fields is introduced. The floor field is a secondary two dimensional grid which has the same dimensions as the movement matrix. In this model's case all floor fields are defined as discrete grids, each cell of the grid holding a numerical value. In this model, two floor fields are defined;

[3] Each time-step a pedestrian will move 40 centimeters. The average walking speed of a person is 1.3 m/s, which makes every time-step 0.3 seconds. This matches with the normal reaction time of a person.

dynamic and static floor fields.



(a) Static Field for a 63×63 cells floor with one exit in the middle of the northern wall.

(b) Static Field for 63×63 cells and four exits, one in the middle of each wall.

Figure 4: Different configurations of static field. The maximum values can be seen at the doors.

3.3.1 Static Floor Field $\mathcal{S}$

The static floor field $\mathcal{S}$ is a gradient of values which has a maximum at given attraction points. The magnitude of the field depends on the distance of the cell to the attraction points. This field is unchanged in time and thus does not evolve nor is it affected by pedestrian movement. The static floor field is used to simulate points in space with great attractiveness to pedestrians, such as windows or exit doors. In this specific project the $\mathcal{S}$ field will describe the shortest path to the single exit door available. In another way, we can see the static field mimic an attractive force that becomes higher as one approaches the attractive region and it can be seen as a sort of gravitational pull. The static field constructing algorithm is dependant on the distance of the cells to the doors and is at follows.

The movement floor is surrounded by impenetrable obstacle cells, effectively enclosing the room within four walls. Doors will be defined as transversable cells incrusted within the wall. The coordinates of the n-amount of doors is given by $[(i_{d0}, j_{d0}), \ldots, (i_{dn}, j_{dn})]$. A pedestrian is considered to be rescued when it stands on one of these door coordinates, and thus can only exit the room through them. The explicit values of $\mathcal{S}$ are given by a space metric.

For the door number l, the distance to each cell (i, j) is calculated with equation 1.

$$M_l(i,j) = \sqrt{(i_{dl} - i)^2 + (j_{dl} - j)^2} \tag{1}$$

We run this equation for all cells in the floor and find the cell furthest away from the door l. The distance between the cell and the door is saved as M_l^{max}. A temporary static field is created for each door. So for n doors, n temporary static fields will be created. For the temporary static field l, the value of each of its cells is given by equation 2.

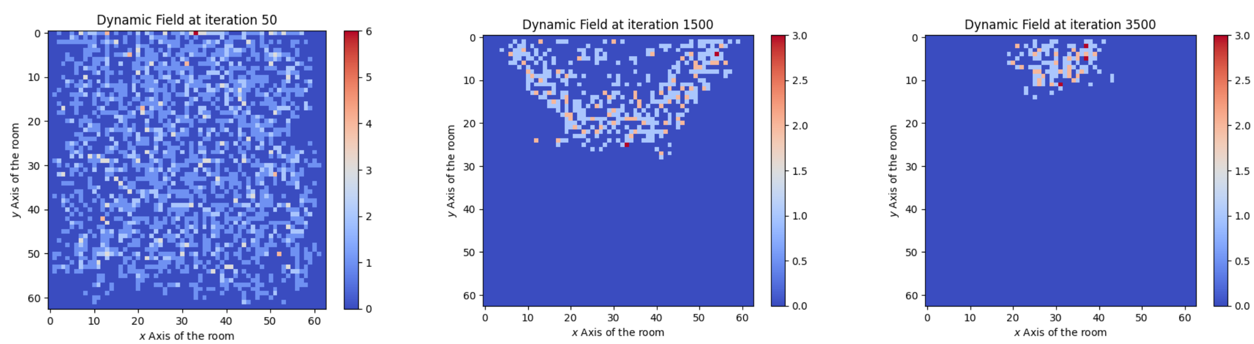
$$S_l(i,j) = M_l^{max} - \sqrt{(i_{dl} - i)^2 + (j_{dl} - j)^2} \tag{2}$$

We now have l amount of temporary static field lattices. The final static field is calculated from the temporary static fields in such way that the minimum value for each cell is chosen from the temporary static fields, as shown in equation 3.

$$\mathcal{S}(i,j) = min_l(S_l(i,j)) \tag{3}$$

A code snippet on the calculation of the static floor field can be seen at annex A.

3.3.2 Dynamic Floor Field $\mathcal{D}$



(a) Dynamic Field's values at the 50^{th} iteration of the simulation.

(b) Dynamic Field's values at the 1500^{th} iteration of the simulation.

(c) Dynamic Field's values at the 3500^{th} iteration of the simulation.

Figure 5: Typical values of the dynamic field throughout a simulation of an evacuation with one single door. The floor has a size of 63×63 cells, it is filled at 30% capacity. The simulation was run with $\alpha = 0.3$, $\delta = 0.3$, $k_{\mathcal{S}} = 0.4$ and $k_{\mathcal{D}} = 1.0$

The idea of the dynamic field is inspired by the phenomenon of chemotaxis, where some insects such as ants will follow a pheromone trail left by others [4]. It is a matrix of the same dimensions as the previous floor field which will hold numerical values. These numerical values will be affected by the pedestrian's movements and will change throughout the evacuation process. The dynamic floor field is created to model far away interactions between pedestrians in such a way that pedestrians do not need information from any other cell, rather only its neighbors.

The dynamic floor field $\mathcal{D}$ is initialized as a grid of zeros. This field is subject to a series of updates that will modify the cell's values. The pedestrians can change values of the field by increasing the value of the cell they were on before a move. As such, a pedestrian whom moves from cell (i, j) to a neighboring cell will increase $\mathcal{D}(i, j) \to \mathcal{D}(i, j) + 1$. The dynamic field is affected only by moving pedestrians and corresponds to a speed field. Thus, the dynamic field is an integer field, which has been compared to a "bosonic field" in Kirchner et al. model [4]. In this definition, an increase or decrease in the magnitude of the dynamic field corresponds to the cell's bosons quantity changing due to its dynamics. With this same choice of terminology, pedestrians have fermionic qualities since they behave according to an exclusion principle (one cell can inhabit one single pedestrian). The dynamic field's cell's contents will be here referred as "steps".

The dynamic field is also subject to decay and diffuse. Decay refers to the dynamic that any cell could decrease its value by one. The probability of decay is ruled by the parameter $\delta \in [0, 1]$. Diffusion refers to the act of a cell decreasing its dynamic field value by one and increasing a neighbor's dynamic field value by one. The probability of diffusion is given by $\alpha \in [0, 1]$. The decay and diffusion model how in a real-life scenario most transited paths will change throughout time. A step having a decay dynamic reflects how the relevant steps for an evacuation will be the most recently left. "Old" steps, or steps taken at the beginning of the simulation will not have relevance for mid-simulation movements. Since the evacuation dynamics will alter the environment of the room, efficient evacuation paths will evolve [1][4]. This will require old steps to decay. The diffusion of the dynamic field's steps can be interpreted as broadening of the path. There is no perfectly defined path, but merely a neighborhood of cells which show a transited region. The decay and diffusion of the dynamic field simulate the broadening and disappearance of "old" steps, and so the dynamic field is destined to fully decay.

In every update of the simulation process, all cells of the dynamic field are prone to both decay and diffusion. From a single cell with a magnitude k, the k steps will have a chance to decay or diffuse. Steps will have a probability δ of decay and α of diffusion. Decay means that the value of the cell decreases one. Diffusion is defined as the magnitude of the cell decreasing one and increasing the value of one random neighbor by one.

Explicitly, the update of $\mathcal{D}$ is as follows. A dynamic field cell $C_{\mathcal{D}}(i, j)$ holds k steps. Firstly, we will apply the decay dynamic. In this case, we run k times the chance that the decay will happen. If the decay parameter is $\delta = 0.3$, then there is the chance that 30% of the steps in the cell will decay. In this example, let us say that from k steps, l steps decay. In this case the number of steps that decay will always be less or equal to the initial amount of steps the cell held, $l <= k$.

Afterwards, we will run the diffusion mechanic. In the cell $C_{\mathcal{D}}(i, j)$ there are now $k - l$ steps. Thus, from these steps that are left, we will run now the chance that diffusion will happen based on the parameter α. At the end of an update, $C_{\mathcal{D}}(i, j)$ will hold non-negative values, thus the dynamic field is a discrete array of integer values. More details on the dynamics can be seen in annex B.

3.4 Transition Probability

The transition probability of a pedestrian to move to a cell with coordinates (i, j) will be dependent on:

1. The value of the dynamic field $\mathcal{D}(i, j)$. Since the value of the cell is modified by the motion of other pedestrians, this simulates an attraction to highly transited areas. This models herding behavior, where pedestrians will create a singular moving mass.

2. The value of the static field $\mathcal{S}(i, j)$, which will attract pedestrians to points of interest. In the case of the model such points are exits, and thus this field will aid in modelling an evacuation process.

3. The occupation number of the cell $\chi(i, j)$, will indicate if the cell is either occupied by a pedestrian, a wall or an obstacle.

The probability function to move to the cell (i, j) is given by [4]:

$$p(i, j) = N e^{k_{\mathcal{D}} \mathcal{D}(i,j)} e^{k_{\mathcal{S}} \mathcal{S}(i,j)} \chi(i, j), \tag{4}$$

where $\chi(i, j)$ is:

$$\chi(i, j) = \begin{cases} 1 & \text{if } (i, j) \text{ is empty} \\ 0 & \text{if } (i, j) \text{ is occupied by a pedestrian, wall or an obstacle.} \end{cases} \tag{5}$$

where N is a normalization constant to ensure that:

$$\sum_{Neighbors} p(i, j) = 1 \tag{6}$$

$k_{\mathcal{D}} \in [0, \infty)$ and $k_{\mathcal{S}} \in [0, \infty)$ are sensitivity parameters which will weight the effect that the floor fields have on the transition probabilities. These are global and will have the same value for all pedestrians.

This definition of the probability function will create an exponential attraction to the fields. So, the closer the pedestrians are to the door, the higher the attraction to it. A pedestrian will have five transition probabilities; north, west, south, east and center (stay and not move). The transition matrix (figure 6) shows the transition probabilities of the pedestrian.

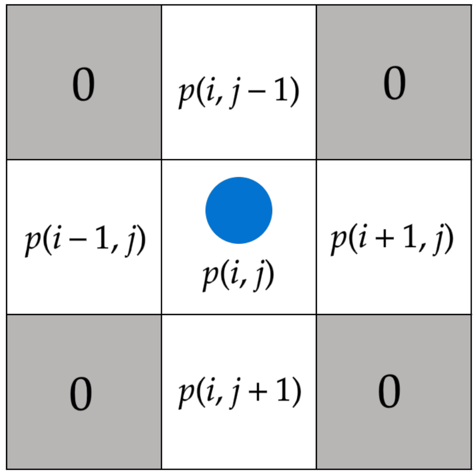


Figure 6: Transition probabilities for the immediate neighbors of the pedestrian (shown in blue).

3.5 Update Rules

The update rules of the model can be now defined. These are followed in this order every time-step and are run in parallel, simultaneously for all pedestrians. Thus, all pedestrians make one step simultaneously, and there are no priorities given.

1. The dynamic field $\mathcal{D}$ is updated with its decay and diffusion dynamics (Section 3.3.2 and annex B).

2. For each pedestrian all transition probabilities are calculated using equation (4).

3. With the usage of a probabilistic algorithm (shown explicitly in Annex C), each pedestrian chooses a desired movement based upon their individual transition matrix. Pedestrians are thus inclined to move to high-probability cells.

4. Conflicts may arise when two or more pedestrians wish to move to the same cell. This is resolved with a probabilistic method explicitly shown in Annex C. A selected pedestrian will execute its move while the rest of the pedestrians will not move in this turn.

5. The dynamic field $\mathcal{D}$ is increased by all moving pedestrians following the rule established in section 3.3.2.

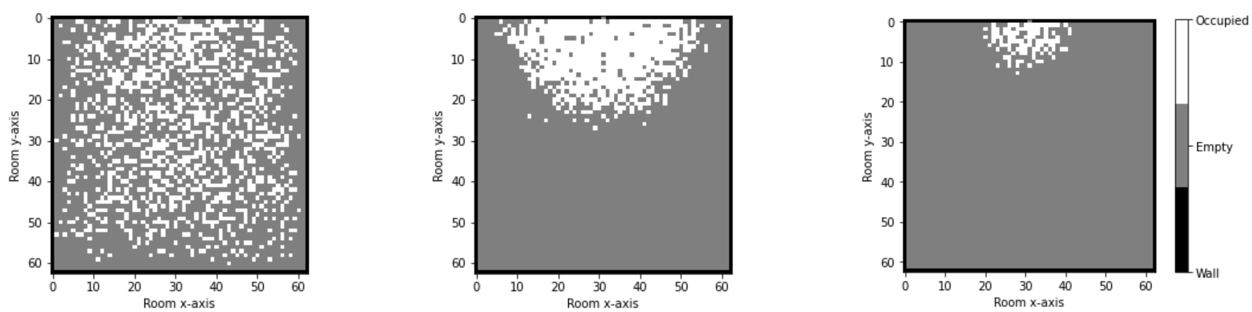
It is also noted that pedestrians will be subject to a dynamic field correction. This is needed since particles may become confused by their own trail in the dynamic field. Thus, a correction is added where we ignore the pedestrian's previous contribution to the dynamic field when we calculate the transition probabilities. If the correction is not added, pedestrians may engage in an oscillatory motion where they will walk back and forth in a pattern that showcases that they are trying to follow their own trail.

These updates will continue until all pedestrians are saved. A pedestrian is considered as saved when it steps on the cells identified as "doors".

These rules create a semi-Markovian process. The future state of the pedestrian is not dependent on the previous states it held, thus no sense of inertia is given. The only memory the particle has is of its previous step in order to process the correction. The system is stochastic since several steps of the update process depend on random number generators. Even so, these simple rules allow us to replicate collective emergent phenomena found in real-life scenarios. This is done with lesser computational burden, which allows us to model greater numbers of pedestrians in increasingly complex scenarios.

4 Features of the Model

4.1 Pedestrian Behavior



(a) Iteration 50 (b) Iteration 1500 (c) Iteration 3500

Figure 7: Typical movement scenarios for an evacuation process of a big room. This room is 63 x 63 cells in dimension, with a single door in the northern wall. The white cells represent a pedestrian present, grey cells are empty and black cells are occupied by an impenetrable wall. This simulation took approximately 3800 iterations for a full evacuation (100% of pedestrians evacuated)

Full evacuation is the simulation's goal, and this is defined as having 100% of pedestrians as saved by exiting through the door(s). All the model's variables are shown explicitly in table 1, and all of them are set at the beginning of the simulation, and will not change for that evacuation scenario. The pedestrians are initially placed uniformly randomly throughout the movement field, such that the initial pedestrian density configuration in the floor is as shown in Figure 7a. The movement field is surrounded by an impenetrable border, which we will call wall, from which there will be some open cells which we will refer as doors. The pedestrians will make their moves, such that in every iteration each pedestrian will make a maximum of one step. The velocity of the pedestrians then is limited by $v_{max} = 1$.

In an ordinary evacuation scenario, in which pedestrians are coupled to both the static field and the dynamic field

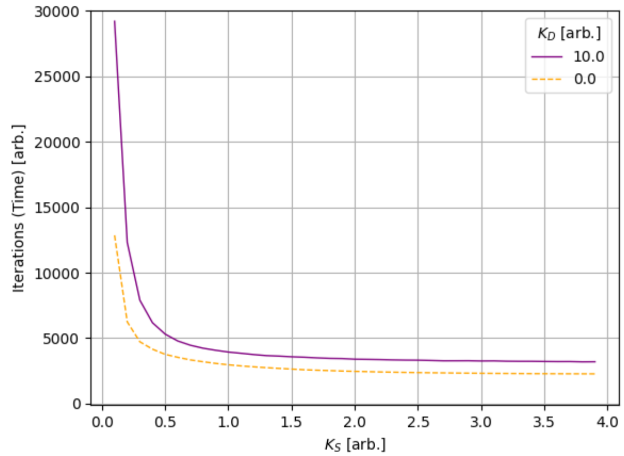
Parameter	Allowed values	Properties
x	[2,∞)	Length of the room
y	[2,∞)	Width of the room
ρ	[0,1]	Initial population density of the room. 0.1 refers to 10% of the room initially randomly filled, and so on.
α	[0,1]	Diffusion probability of a step in a dynamic field cell. 0.1 refers to a 10% diffusion probability.
δ	[0,1]	Decay probability of a step on a dynamic field cell.
$k_{\mathcal{S}}$	[0, ∞)	Sensitivity parameter related to the static field. Weights the contribution the static field's values have to the result of the transition probability shown in equation (4).
$k_{\mathcal{D}}$	[0, ∞)	Sensitivity parameter related to the dynamic field. Weights the contribution of the dynamic field to the transition probability.

Table 1: Simulation variables which are implemented at the start of the simulation and will stay constant until the evacuation has been finished.

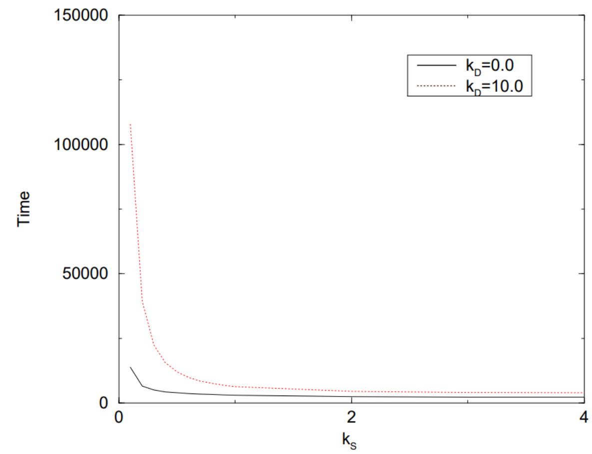
by their values of $k_{\mathcal{S}}$ and $k_{\mathcal{D}}$, the pedestrians will approach the door in order to minimize their distance to it. As pedestrians approach the door, a semi-circle around the door will be created (figure 7b). Here, pedestrians will exit through the door one by one. This will cause a radial movement of empty spaces from the door to the edge of the ”circle” [4]. As the semi-circle is formed, the radius of it will diminish as more pedestrians exit (figure 7c).

4.2 Impact of Sensitivity Parameters on Evacuation Times

The sensitivity parameters $k_{\mathcal{S}}$ and $k_{\mathcal{D}}$ are variables that are set at the beginning of the simulation and will affect the behavior of the model substantially. These sensitivity parameters will determine the influence that the floor fields have on the pedestrian's transition probabilities and thus, on their movements. Using different parameter pairs will affect evacuation times. Figures 8 and 9 showcase graphs which will explain the behavior of different sensitivity parameter pairs. Each data point is the average of 40 evacuation processes completed with that specific sensitivity parameter pair.

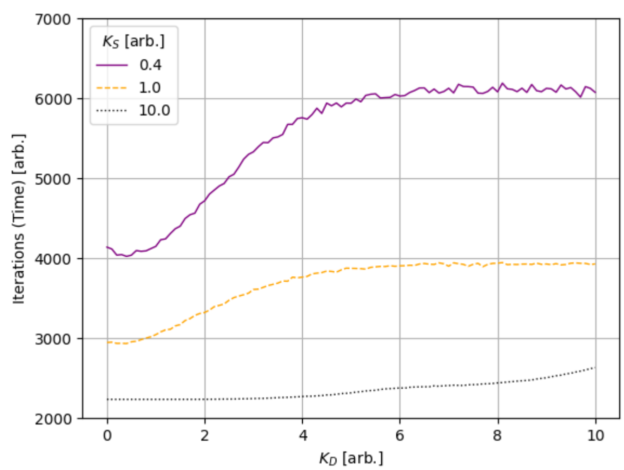


(a) $\delta = 0.3$, $\alpha = 0.1$, $\rho = 0.3$

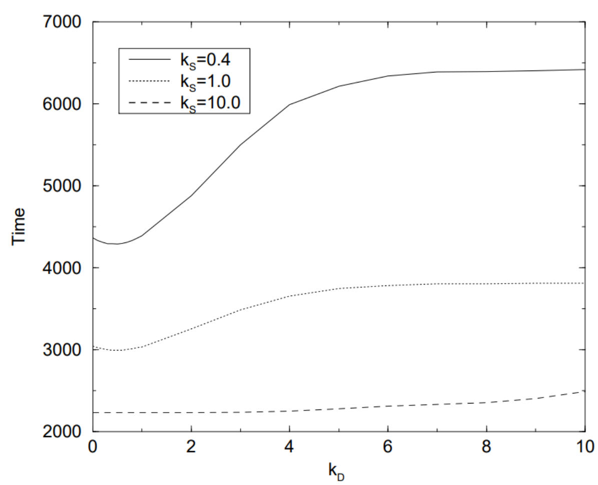


(b) Figure 5a from Kirchner's et al. (2002) paper results.

Figure 8: Averaged evacuation times for different values of the sensitivity parameters. These averages are for evacuations of a 63 $\times$ 63 room with a single door in the northern wall. Both graphs have the exact same parameters. Figure 8a has been made with this thesis' implementation of the FFCA model. 8b is the result shown in [4].



(a) $\delta = 0.3$, $\alpha = 0.3$, $\rho = 0.3$



(b) Figure 5b from Kirchner's et al. paper results. [4]

Figure 9: Averaged evacuation times for different values of the sensitivity parameters leaving $k_{\mathcal{S}}$ as a constant. These averages are for evacuations of a 63 $\times$ 63 room with a single door right in the middle of the northern wall. Here again, the graph shown in 9a is the averages gotten from this thesis' implementation of the code. The graph shown in 9b is the result of Kirchner's et al. paper [4]

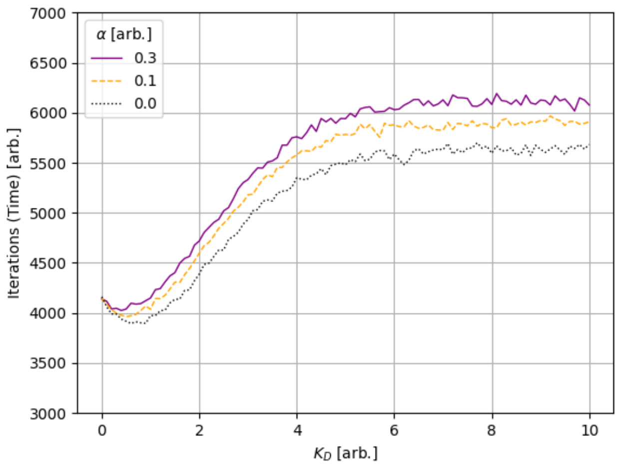
These evacuation times are the ones for a 63 $\times$ 63 cells matrix, with a single northern door of width on a single cell right in the middle and with an initial population density of ρ = 0.3. In Figure 8a we can observe how the parameter $k_{\mathcal{S}}$ will affect evacuation times by changing it as we keep the parameter $k_{\mathcal{D}}$ constant. In this case, we can see a clear relationship between increasing $k_{\mathcal{S}}$ and diminishing evacuation times regardless of the value of $k_{\mathcal{D}}$. For a vanishing $k_{\mathcal{S}}$, the pedestrians have no information about the magnitude of the static field, and thus have no information about the location of the door. The pedestrians will then conduct a random walk until, by mere chance, some may escape through the door. Thus, the parameter $k_{\mathcal{D}}$ will affect evacuation times creating confusion, by deviating pedestrians from a direct path to the door. Comparing Figure 8a to Figure 8b we can see a qualitative and quantitative similarity between this thesis' implemented model and Kirchner's model. It is noted that in this thesis paper we evaluated from $k_{\mathcal{S}} \in [0.1, 3.9]$, and not directly from 0. This explains the deviation at the beginning of the data set, where in figure 8b iterations increase until around the 100,000.

Figure 9 showcases the averaged evacuation times where we left $k_{\mathcal{S}}$ static and evaluated evacuation times as function of $k_{\mathcal{D}}$ for every scenario. It is observed that regardless of the value of $k_{\mathcal{S}}$, as $k_{\mathcal{D}}$ is increased the evacuation times will increase until plateauing. For comparably small values of $k_{\mathcal{S}}$ (0.4 and 1.0), we can observe a non-monotonic minimum at a specific combination of parameters. This suggests that, for a small value of $k_{\mathcal{S}}$, pedestrians will find useful information in the dynamic field which will diminish the amount of steps to get to the door. The pedestrians use the information of places with the most amount of flow and use it in order to evacuate faster. This effect is not found for higher values of $k_{\mathcal{S}}$ (10.0). From this graph we can define a pair of parameters which will cause a non-monotonic evacuation minimum for small values of $k_{\mathcal{S}}$, which may nudge to an optimization problem. Again, this thesis model's results are seen in Figure 9a which we compare to Kirchner's et al. results in Figure 9b. We see a significant qualitative similarity, which showcases that this thesis' implementation of the FFCA model has the expected features.

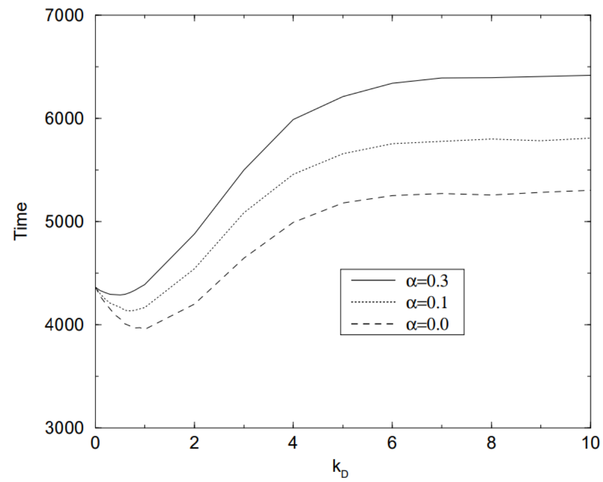
From these two figures we can conclude that for higher values of $k_{\mathcal{S}}$, we will minimize the evacuation times since pedestrians will hold a high amount of information of the positioning of the door. $k_{\mathcal{S}}$ is the degree of knowledge the pedestrians have of their surroundings or the geometry of the room. For low $k_{\mathcal{S}}$ the pedestrians have limited knowledge of the location of the exits, thus increasing number of steps needed in order to approach the door. For low values of $k_{\mathcal{S}}$, equivalent small values of $k_{\mathcal{D}}$ will cause a minimum in average evacuation times. But, for high values $k_{\mathcal{D}}$ becomes noise and increases evacuation times since pedestrians will follow zones of high transit instead of directing themselves to the door.

Situations with a low value of $k_{\mathcal{S}}$ are such where the door is not visible, due to smoke, fire, or a very dense crowd blocking sight of the exit. Situations where $k_{\mathcal{D}}$ is high models herding behaviors, such as when pedestrians do not know the location of the exit and hope to escape by following the bigger mass supposing that in that mass at least some of them may know where the exit is. Depending on the combinations of values imposed at the beginning of the simulation for $k_{\mathcal{S}}$ and $k_{\mathcal{D}}$ we can simulate different evacuation scenarios. For vanishing $k_{\mathcal{S}}$, the location of the door is unknown, thus could be used to model smoke-filled or darkened rooms.

4.3 Studying the Effect of α and δ in Evacuation Times

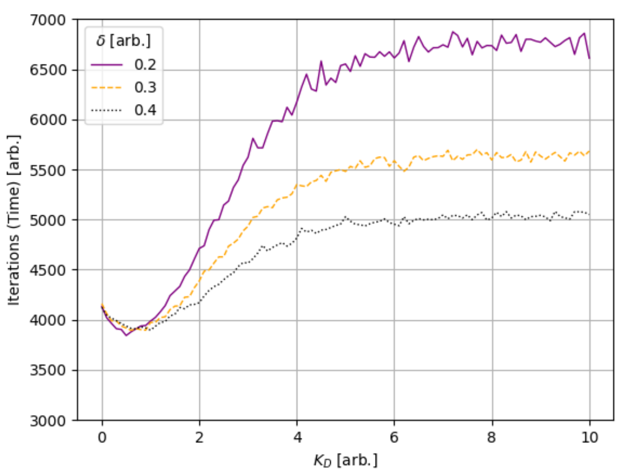


(a) Averages for simulation with $k_{\mathcal{S}} = 0.4$, $\rho = 0.3$ and $\delta = 0.3$.

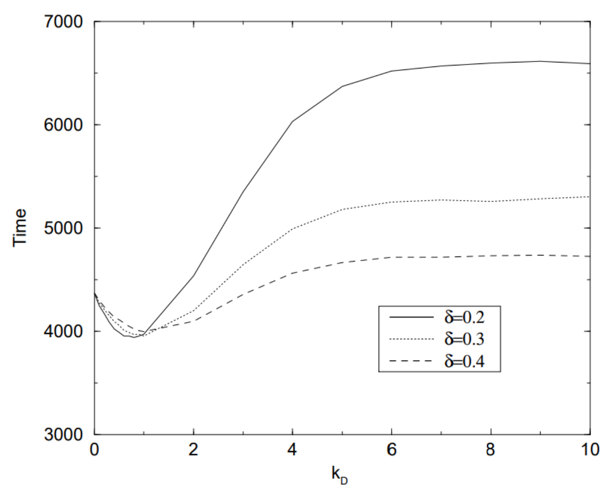


(b) Figure 7a from Kirchner's et al. paper results.

Figure 10: Averaged evacuation times for different values of α. These averages are for evacuations of a 63 $\times$ 63 room with a single door in the northern wall. Both graphs have the exact same parameters. Figure 10a has been made with this thesis' implementation of the FFCA model. 10b is the result shown in [4].



(a) Averages for simulation with $k_{\mathcal{S}} = 0.4$, $\rho = 0.3$ and $\alpha = 0.0$.

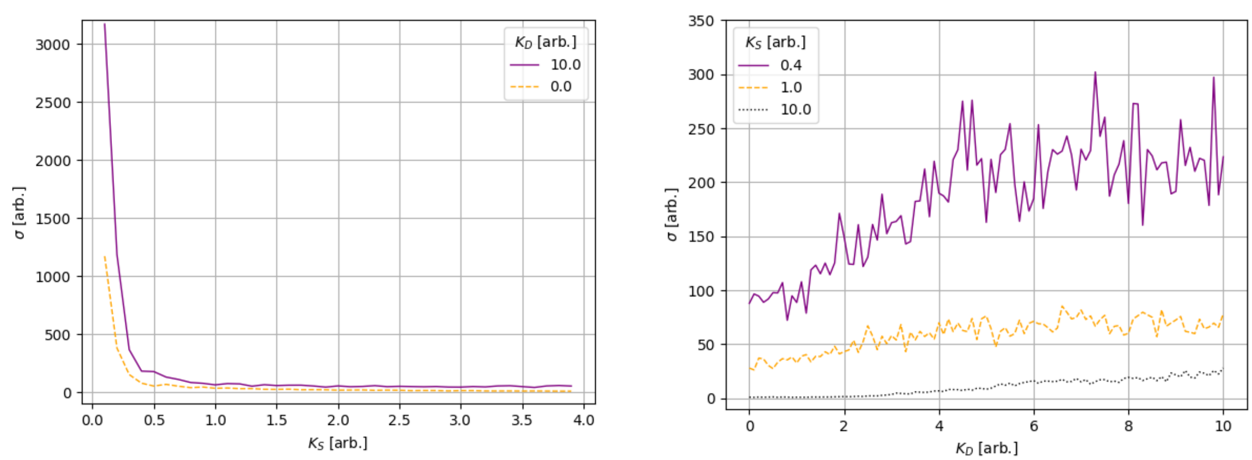


(b) Figure 7b from Kirchner's et al. paper results.

Figure 11: Averaged evacuation times for different values of δ. These averages are for evacuations of a 63 $\times$ 63 room with a single door in the northern wall. Both graphs have the exact same parameters. Figure 11a has been made with this thesis' implementation of the FFCA model. 11b is the result shown in [4].

Since $k_{\mathcal{D}}$ and the dynamic field $\mathcal{D}$ will affect evacuation times, it becomes apparent that the diffusion parameter α and the decay parameter δ will also affect evacuation times since they will regulate how the dynamic field's values evolve. Figure 10 showcases how different values of α, the probability of diffusion of the dynamic field, will affect evacuation times. Since diffusion will broaden the path, it will make following the path take more steps since the path is now wider. This will relate to longer average evacuation times, as shown in Figure 10a which values are the result of this thesis implementation of the model. We compare our results to Kirchner's model's results shown in Figure 10b. There are qualitative similarities between graphs, most importantly the non-monotonic minimum.

The decay parameter δ will rule over the decay rate of the dynamic field's values. Since Figure 11 was done for a low value of $k_{\mathcal{S}} = 0.4$, most information will be gotten by the dynamic field. Thus, a rapid decay will result in loss of most steps, and locations with high step density will end up being zones with high, constant flow of pedestrians. This will quickly erase the dynamic field's cell's values where pedestrians do not constantly transit, thus erasing this unnecessary noise from evacuation dynamics. This can be seen in Figure 10a, where for the lowest decay probability (δ = 0.2) the average evacuation times are the highest average. Comparing this thesis' implementation of the FFCA Kirchner et al.'s model to the original paper, we can observe the same qualitative behaviors albeit with variations in the quantitative values. A different implementation of the dynamic field, or stochastic error may be probable causes of the disparity. The minimums for evacuation times are seen for low values of $k_{\mathcal{D}}$ regardless of δ values. For values of $k_{\mathcal{D}}$ higher than those of $k_{\mathcal{S}}$ the extra information becomes noise regardless of the value of δ or α. High values of $k_{\mathcal{D}}$ then, may serve as a way to simulate high-stress panic scenarios, where people will stop rationalizing behaviors and run in an aimless herd, which has been seen in real-life scenarios [1]. As a final definition, low values of $k_{\mathcal{D}}$ model the normal urge pedestrians have to follow masses of other pedestrians. For high values, $k_{\mathcal{D}}$ will cause aimless herding of pedestrians, even when this decision seems illogical, which is similar to a high-stress scenario.



(a) Standard deviation graph of the evacuation times shown in figure 8a

(b) Standard deviation graph of the evacuation times shown in figure 9a

Figure 12: Standard deviation of evacuation times for a large room.

The evacuation times will vary between simulations, and thus depend also on the sensitivity parameters. In Figure

12a we see a strong dependence between higher values of $k_{\mathcal{S}}$ and lower standard deviation of evacuation times. This suggests that for high knowledge of the position of the exits, the evacuation process will be almost deterministic, in which the evacuation time will not vary, regardless of the initial position of the pedestrians. $k_{\mathcal{D}}$ will inevitably increase the standard deviation of the data sets, since pedestrians will follow one another, increasing evacuation times randomly. Thus, a high $k_{\mathcal{D}}$ would simulate a scenario where stochastic movement occurs, such as a high-panic scenario.

4.4 Definition of Regimes

From this analysis, we will now define evacuation regimes, firstly introduced in [4]. An evacuation regime will be defined as a combination of sensitivity parameters such that they will create different evacuation scenarios. In a sense, these regimes can be seen as different phase states of the system, in which the particles will have a different density and average speed due to an increase in these ”temperatures”. The *Ordered Regime* is defined as when the only information that pedestrians use for their decision making comes from the static floor field, so from the door's ”attraction field”. In this case, $k_{\mathcal{D}} = 0$ and $k_{\mathcal{S}} > 0$. The term Ordered comes from the fact that this regime is the one which has the least standard deviation (as shown in Figure 12a) and thus is almost deterministic in the meaning that the evacuation times will not vary much regardless of the initial pedestrian configuration. This regime can be translated as a low-panic evacuation process, but very idealized as in which pedestrians will not notice one another at all.

The *Optimal Regime* couples pedestrians to both the dynamic field and the static field. In Figure 8 we see that in cases where $k_{\mathcal{S}}$ has low values (0.4 and 1.0), the absolute evacuation minimum does not exist when $k_{\mathcal{D}} = 0$, but when there is a value such that $0 < k_{\mathcal{D}} < k_{\mathcal{S}}$. It is also noted that in Kirchner et al. (2014) it is mentioned that ”[The evacuation minimum] . . . vanishes again for very weak coupling to S ($k_{\mathcal{S}}$ = 0.1 . . .) where the movement of the pedestrians is similar to a random walk.” (p. 268) [4]. So, the optimal regime is found very seldom in very specific values of $k_{\mathcal{S}}$ and $k_{\mathcal{D}}$. It is also noted that in Figures 10 and 11 the minimums of evacuation times will vary depending on the values of α and δ. Thus, the Optimal regime is a point of minimum evacuation for a range of $0.1 < k_{\mathcal{S}} \leq 1.0$ at least. The specific range of $k_{\mathcal{S}}$ where this optimal regime is found has not been yet delimited. This regime is potentially the most close-to-life regime where pedestrians are influenced both by the static field and by the dynamic field but in such a way that their movements are not fully deterministic but also not fully stochastic.

Finally the *Disordered Regime* occurs when there is a strong coupling to the dynamic field such that $k_{\mathcal{S}} << k_{\mathcal{D}}$. This maximizes both evacuation time and the standard deviation, thus the Disordered regime creates an stochastic, random movement of pedestrians in which escape is only achieved when the particles find, almost by mere chance, the door. We note that $0 < k_{\mathcal{S}}$ since if there is no attraction at all to the door, then the evacuation process will tend to never be completed. This is a regime that models a high-stress, zero-visibility evacuation process which will make pedestrians run in random panic. The three regimes will serve useful to model different scenarios where the stochasticity of pedestrian movements will differ. A higher coupling to $\mathcal{D}$ will increase evacuation times regardless of α and δ values as seen in Figures 10 and 11. The resumed definitions of the different regimes are noted in Table 2.

Clearly, evacuation times will also be affected by parameters such as α and δ, but we have seen and confirmed that, regardless of α and δ, a change of sensitivity parameters will affect evacuation times. We have also concluded that $k_{\mathcal{S}}$ and $k_{\mathcal{D}}$ will directly affect the behavior of pedestrians by changing the possible results of their transition probabilities, impacting explicitly on the pedestrian's decision making. This is the closest to affecting the pedestrian's stress level and awareness, which in a real-life scenario could be a measurable variable. Values of α and δ cannot be measured or controlled, and will serve only to create realistic paths. In this case, α and δ are set as constants.

Regimes	Parameters	Description
Ordered	$k_{\mathcal{D}} = 0\,,\ k_{\mathcal{S}} > 0$	Absolute minimum of evacuation where pedestrians do not have interaction between them due to the dynamic field and are only attracted to the exit.
Optimal	$k_{\mathcal{D}} < k_{\mathcal{S}}$	Minimum of evacuation for a realistic scenario where pedestrians are both attracted to the door and also to high-flow regions in the floor.
Disordered	$k_{\mathcal{D}} >> k_{\mathcal{S}}$	Maximum of evacuation for a high-panic scenario where pedestrians are barely attracted to the door's static field and will follow high-density flows of pedestrians creating a random walk.

Table 2: Definition of evacuation regimes based upon pairs of sensitivity parameters.

Seeing as the model is strongly influenced by the sensitivity parameters, a modification to them will change the behavior of evacuation processes. This model, until now a replica of Kirchner's et al. FFCA model, assumes a homogeneous mass of people, all of them with the same degree of knowledge of the position of the door and as well the same tendency to follow the places of higher flow. In order to inch closer to a near-to-life simulation, we need to consider that in a real life evacuation process the crowd is non-homogeneous in such a way that not all pedestrians have the same degree of knowledge of the location of the door, or the same "stress-levels". Thus, heterogeneity in a crowd is a good approach for new pedestrian behaviors. In this thesis we introduce the new Grouped Sensitivity Parameters FFCA (GSP FFCA) model, in which we introduce pedestrian groups which will be affected by different pairs of sensitivity parameters $k_{\mathcal{S}}$ and $k_{\mathcal{D}}$. This expects to model how in a mass of people not everyone will hold the same amount of knowledge of the location of the door or have the same urgency to follow the crowd.

5 Proposed Model for Grouped Sensitivity Parameters

1. I escaped according to the signs and instructions, and also broadcast or guide by shopgirls (46.7%).
2. I chose the opposite direction to the smoking area to escape from the fire as soon as possible (26.3%).
3. I used the door because it was the nearest one (16.7%).
4. I just followed the other persons (3.0%).
5. I avoided the direction where many other persons go (3.0%).
6. There was a big window near the door and you could see outside. It was the most "bright" door, so I used it (2.3%).
7. I chose the door which I'm used to (1.7%).

Figure 13: Survey of 300 people after a fire drill conducted in a large supermarket in Japan. Conducted and published by K. Abe, "Human Science of Panic" (translated from Japanese), Brain Pub. Co., Tokyo, 1986. Full reference at [23]

Most research which bases themselves on tweaked FFCA models for evacuation assume a homogeneous crowd. Meaning, all pedestrians have the same parameters and will be affected the same by the environment [9] [18] [13] [14] [15]. This simplifies the scenario assuming all pedestrians in an evacuation may have the same knowledge of the door or feel the same attraction to zones of high flow. In reality pedestrians will choose their moves due to different reasons, as it is shown by Nishinari et al. ([23]) survey shown in Figure 13. We can identify that answer (1) "*I escaped according to the signs and instructions and also broadcast or guide by shop-girls*" is the majority, and assumes that a room will be well signalized and also that the signs are visible. In the same fashion, answer (6) requires a visible, unobstructed shining window. Second answer, "*I chose the opposite direction to the smoking area[...]*" works when the fire or smoke source is defined, and not when the visibility is so low that the smoke may seem to irradiate from everywhere. The third answer also depends on visibility and awareness of the door's position in the room. Reasons (4), (5) and (7) depend strongly on the pedestrian's memory and previous experience of the room, either following the individual's own experiences or by following other's movements, thus trusting someone else's experience. If the visibility worsens, due to electricity failing due to fire or earthquake or due to smoke, dust or debris, people who chose their moves as manifested in answer (1) and (2) would be forced to fall into other decision-making options. Thus, we can see that pedestrian evacuation groups are hardly homogeneous, and since this survey was done in a relatively low-stress scenario it may not reflect how people may behave when presented with a high risk evacuation.

Studies on the evacuation dynamics of heterogeneous crowds have been initiated [24]. Muller et al. proposed initial heterogeneous evacuation processes such as the evacuation of asymmetrical pairs which are based upon strong relations between a pedestrian pair [9]. In this model, pedestrians pairs consist of a leader and a follower, which are based upon parent-child relationships. The leader will be the only one contributing to the dynamic field with dropped bosons (steps). These steps are divided in two types; public and group specific. Leaders interact between each other via the public steps, while only a leader's follower can read the group-specific steps. The idea of dynamic group fields is also introduced, where a pedestrian population is comprised from N-pedestrian groups. These N-pedestrian groups all have the same size. Pedestrians from a group i can only access dynamic field steps which were dropped by a group member. This results in several herding groups which follow one another in the simulation but ignores other group's movement tendencies. Several social groups are then modelled, but it is noted that these groups all have same values of $k_{\mathcal{S}}$ and $k_{\mathcal{D}}$. So, the sensitivity values to both the door and to other pedestrians is the same for all the pedestrian population regardless of their group membership.

In our attempt to model a non-homogeneous crowd, pedestrians will be assigned different pairs of weighting parameters. Pedestrians will be divided into two groups. These two groups will hold different pairs of values for $k_{\mathcal{S}}$ and $k_{\mathcal{D}}$. It is noted that all pedestrians, regardless of the group, will be affected by the same floor fields. This modification has its motivation in modelling the difference in knowledge people may have of the room. One such example of this scenario is a concert. Workers and staff of the venue will be more knowledgeable of the location of exits, while visitors may be more prone to follow the largest group of people. This model adds new variables into the model, listed explicitly in Table 3.

Parameter	Allowed values	Properties
$k_{\mathcal{D}i}$	[0, ∞)	Dynamic sensitivity parameter which weights and couples the dynamic field to pedestrians members of group-i, where i can be 1 or 2.
$k_{\mathcal{S}i}$	[0, ∞)	Static sensitivity parameter which weights and couples the static field to pedestrians members of group-i.
$\tilde{\rho_1}$	[0,1]	Percentage of population total which is part of group 1. The rest of the population will automatically be part of group 2.

Table 3: New variables added to Group Sensitivity Parameters FFCA which will affect the simulation's evolution. These variables are set at the beginning of the simulation and will be constant until the evacuation is completed.

A pedestrian group i is defined as a set of people which will use the set of values k_{Si} and k_{Di} for their decision making processes. In this specific model, i can take the values of [1,2], since we will be working only on dividing the population into two groups. As a difference to Mueller et al.'s model presented in [9], the pedestrians groups will not have a dynamic field associated to them, but will share $\mathcal{D}$ with other pedestrian groups. Since in large evacuation scenarios, such as the one worked here (1116 pedestrians in a 63x63 room), it is expected that people will not follow just their assigned group path. In a panic scenario, it is possible that pedestrians will follow the general most transited path. Still, pedestrians will be attracted in different ways to this path. If pedestrians have visited the venue before for example, the attraction to the most transited path will be lower compared to their attraction to the known position of the door. Here we propose that the Group Sensitivity Parameters FFCA will simulate high-stress evacuation scenarios where there is no communication or coupling to a group in specific. Pedestrians will couple differently to the global floor fields. The specific use of this model reinforces the idea proposed by Mueller. et al. in 2014 that "The diversity of groups and the multiplicity of scenarios such groups can be exposed to show that it is difficult to find a general model which allows efficient computer simulations of pedestrian dynamics for all cases" (p.169).

It is noted that border scenarios are reached when working with limit values of $\tilde{\rho_1}$. If $\tilde{\rho_1} = 0$, then all pedestrians are members of group 2, thus all pedestrians have the same coupling parameters to the dynamic and static field. When $\tilde{\rho_1} = 1$, then all pedestrians will be members of group 1. In these two cases, the model returns to pedestrians having global sensitivity parameter values. We then, are interested in studying middle values of $\tilde{\rho_1}$.

5.1 Results for the Proposed Model

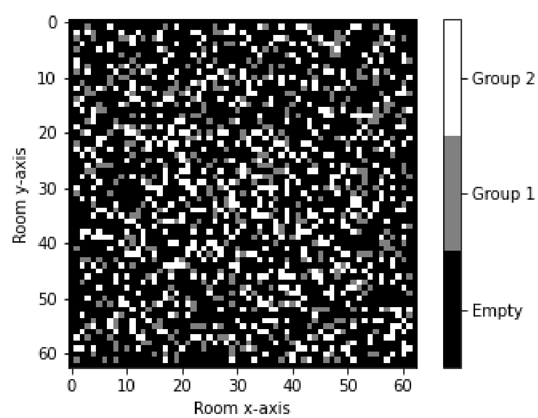
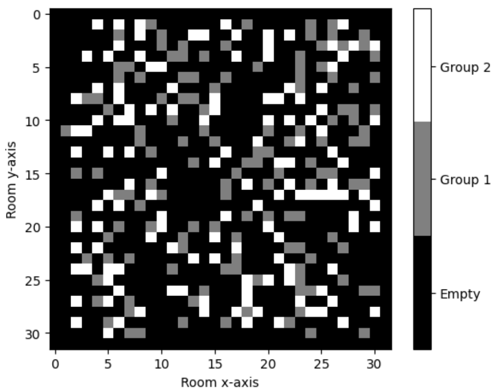
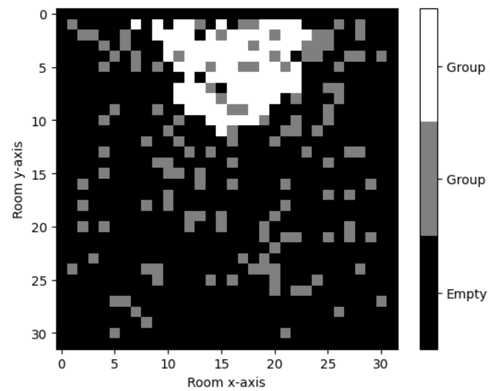


Figure 14: Initial movement configuration for a Group Sensitivity Parameters FFCA model where there is a 50/50 configuration of group 1 and group 2.

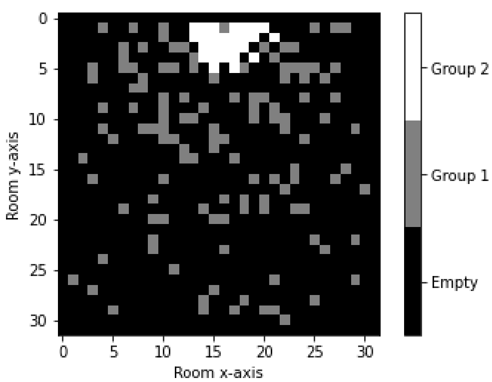
The Group Sensitivity Parameter FFCA model has been implemented with an Object Oriented focus. Every pedestrian in the simulation was given a membership to either group 1 or 2. Pedestrians are initially placed randomly on the floor, regardless of their membership, thus there is a homogeneous mixture of both group 1 and 2 pedestrians as shown in Figure 14. The group's sensitivity parameters will be defined by the regimes seen in Table 2. A group will be defined by its regime, which could be Ordered, Disorganized or Optimal.



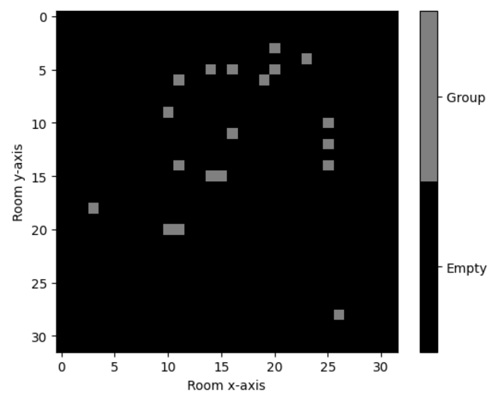
(a) Initial movement configuration for a 50/50 Group configuration between pedestrians in the Ordered (group 2) and Disordered Regime (group 1).



(b) Mid configuration. The pedestrians of group 1 are less aware of the door than pedestrians in group 2.



(c) Movement 260 of the evacuation process.



(d) Movement 5000 of the simulation where the members of group 1 are the only left.

Figure 15: Typical movements for a 50/50 configuration of a GSP FFCA model where pedestrians of group 1 are in an Disordered Regime and group 1 is in the Ordered Regime.

Regime	$k_{\mathcal{S}}$	$k_{\mathcal{D}}$
Optimal	1.0	0.4
Ordered	4.0	0.0
Disordered	0.1	4.0

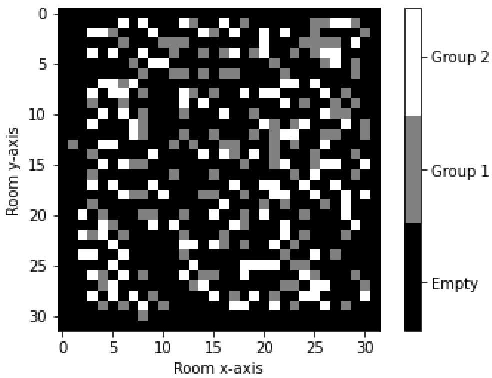
Table 4: Specific values of sensitivity parameters which define the regimes used. This is all defined for $\alpha = \delta = 0.3$.

A group in any of the regimes will hold the sensitivity parameter pair shown in Table 4. Thus, we are now interested in how different group combinations will interact in an evacuation process. The definition for a full evacuation will be when 98% of pedestrians have exited the room. This full evacuation definition is caused by pedestrians who do not exit and will perform a random walk instead of approaching the door, increasing evacuation times to very high values.

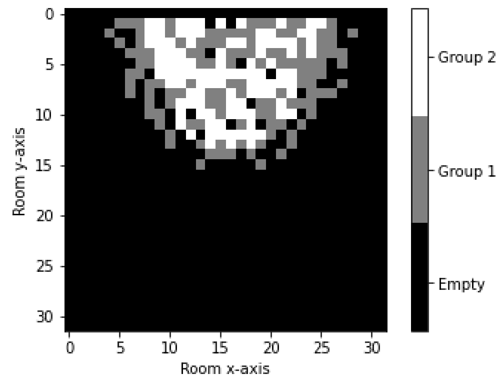
The first group configuration is the Ordered and Disordered configuration as seen in figure 15. Shown is a 50/50 configuration, which translates to $\tilde{\rho_1} = 0.5$. The initial total population is $\rho = 0.3$ and $\alpha = \delta = 0.3$. The room modelled is a 32×32 room with the door in the northern wall. The mid-evacuation configuration showcases that the pedestrians members of group 2 (Ordered Regime) have formed a well defined half-circle at the iteration 100. Meanwhile, pedestrians members of group 1 (Disordered Regime) seem to be conducting a random walk in the middle of the room. Following this, we go now to figure 15c. The pedestrians in group 1 are attracted by the dynamic field formed by the pedestrians in group 2. This is evident since the upper half of the floor has a higher density of pedestrians in the Disordered Regime than the lower half. Finally, iteration 5000 shown in figure 15d shows that after all pedestrians in the Ordered Regime have escaped, pedestrians from the Disordered Regime stay trapped in the room. This is caused by the decay and diffusion of the dynamic field which erases almost all the information which would allow the remaining pedestrians to escape, thus creating a random walk of sorts and increasing evacuation times. This is due to the lack of any memory implemented in pedestrians. In a close-to-life evacuation process, even pedestrians who have no knowledge of the room would eventually find the door's location, due to following the crowd or signaling, and would experience a strong attraction to it. This would cause the formerly lost pedestrians to maintain a close distance to the door and try to approach when possible. It is noted that a 50/50 arrangement of pedestrians in the Optimal and Disordered Regimes will act similarly, as seen in figure 18 found in Annex D.

Screenshots of a simulation process of a 50/50 arrangement of pedestrian groups in the Optimal Regime and Ordered Regime can be seen in figure 16. This is a 32×32 room with $\alpha = \delta = 0.3$ and a single northern middle door. It is noted that the total evacuation process took 609 iterations. The initial configuration is again done in such a way that there is a homogenous mixture of pedestrians in group 1 and 2. Figure 16b showcases a half-circle arrangement formed by particles of both groups. Still, it is noted that the particles closer to the exit are pedestrians members of Group 2, which is the group in the Ordered Regime. This is caused by the group's higher attraction to the door and the lack of any interaction with the dynamic field, which causes them to move to the door in the least amount of iterations. Group 2 will have a head start in the evacuation process and thus we expect that pedestrians members of this group to exit more quickly than the Group 1 counterparts. This is confirmed by Figure 16d, where all members of Group 2 have evacuated leaving remnants of Group 1. Even if pedestrians of Group 2 have a coupling to the dynamic field, most of their interactions are coupled to the static floor field which will allow them to fully evacuate even if the dynamic field fully decays.

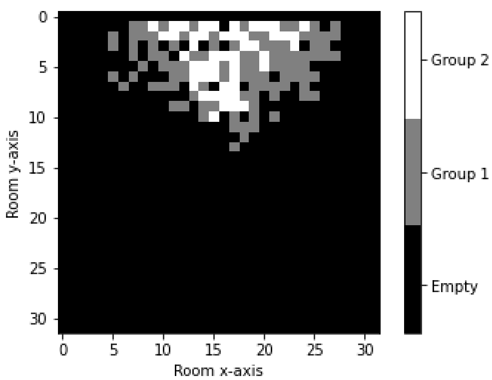
The configurations studied are until now only of equal amounts of pedestrians in Group 1 or Group 2. It is now of interest to explore how is it that total evacuation times will change as a function of $\tilde{\rho_1}$. Figure 17 showcases such functions. Each point is the average of 66 evacuation processes for each Group configuration shown. The Disordered Regime is noted to cause high total evacuation times, which is seen in Figure 17a. The x axis showcases the percentage



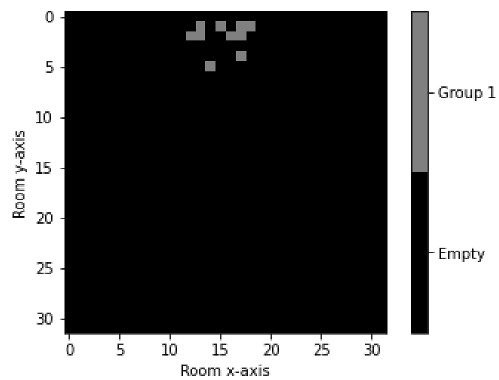
(a) Initial configuration for a 50/50 Optimal (group 1) and Ordered (group 2) evacuation process.



(b) Configuration after 100 iterations.



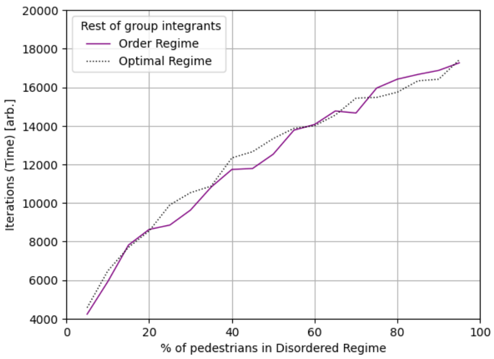
(c) Movement 260 of the evacuation process.



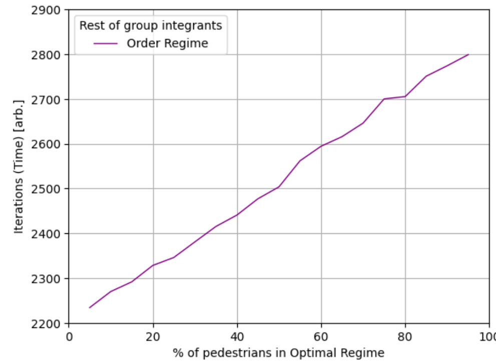
(d) Iteration 600 of the evacuation process, final movements before a total evacuation.

Figure 16: Typical movements for a 50/50 arrangement of a GSP FFCA model where group 1 is in the Optimal Regime and group 2 is in the Ordered Regime.

of the total population which is part of the Disordered Regime group ($\tilde{\rho_1}$). The rest of the population will be conformed by the group established in the legend. Regardless of the population's regimes, the behavior appears to have the same tendency. There is a strong correlation between percentage of the population in the Disordered Regime and the increase in evacuation times. For the limits where $\tilde{\rho_1} \to 1$ and $\tilde{\rho_1} \to 0$, the evacuation times relate to a homogeneous population where all pedestrians are part of one group or the other. Initially, for $0 < \tilde{\rho_1} < 0.2$, there is a rapid increase in iterations. The number of total iterations for evacuation doubles when $\tilde{\rho_1} \approx 0.15$. From this point on, the slope of both the curves decrease. This decrease of the slope goes on until finding a stagnation point around $\tilde{\rho_1} \approx 0.9$. The Disordered Regime will affect evacuation times the most dramatically when their composition is between 0 and 20%. Afterwards, although their increased presence will maximize evacuation times, it seems that after some point there is a saturation. The Disordered Regime group will be increasingly unable to add any more chaos into the evacuation process. It is also noted that, as observed in figures 15 and 18, that the evacuation times will have such high values (>10,000) due to "lost" members of the Disordered Regime which were not able to evacuate before pedestrians of the more knowledgeable group. This causes them to aimlessly roam the room, since the decay and diffusion of the dynamic field leaves them with no information to approach the door. The random walk will only allow these leftover particles to exit the room by mere chance.



(a) Relation between percentage of pedestrians in the Disordered Regime and evacuation time.



(b) Relation between percentage of population in the Optimal Regime and the total evacuation time

Figure 17: Average total evacuation times of different group densities and different regime configurations.

Noting that the evacuation times between populations formed by the Disordered Regimes have extremely high values for their total evacuation times, it has been considered that the direct comparison to populations void of this regime will give no further information. Thus, we focus on the impact that the Optimal Regime will have in an evacuation process which will be populated also by the Ordered Regime. This is shown in figure 17b. The percentage of the population in the Optimal Regime will be increased for every new evacuation process. There seems to be a linear increase in the evacuation times as a function of the population percentage in the Optimal Regime. It is noted that this increase, while linear, does not have a steep slope, thus the rate of change in average evacuation time is not as drastic as the one that occurs in Figure 17a. Still, it appears that having part of the population as a pedestrian group attracted to the dynamic field will not add useful evacuation information, instead, it shows that this extra information added acts as noise. This increases evacuation times and showcases that the Ordered regime will cause the lowest time averages.

6 Project Repository

The Open-Source Initiative pushes for freely accessible source code, which can be used, edited and distributed by anyone and everyone. This pushes for a collaborative effort to develop a software with several, user-made edits. This aims to create a developed, better version of the software. We believe that scientific progress must be open-source. For this present thesis we made the initial objective of creating a coded model in order to replicate the results found in [4]. Afterwards, if the results would have been replicated, we would add ”tweaks” to this code, in order to study how these changes would affect the original Kirchner et al. model.

We find it necessary to make aware that the initial versions of this thesis' code did not produce correct results. This lack of expected results was due to the lack of detail and definitions in the original paper. Dynamics such as decay and diffusion are not gone into detail to, which posed the issue of how exactly diffusion is defined. It is noted that any small change in the definition of these mechanics had a significant impact on the results. Thus, a specific, explicit definition of the dynamics became an objective of this thesis.

More information was searched on different papers which also base their models on Dr. Kirchner's model. The repeating pattern showcases that such definitions of decay, diffusion, "probabilistic methods" and choosing methods are taken for granted to be understood. In [4], there is a mention of java applets which will showcase the working model in which you can make your own simulations. Also, a blog called "ped-net" is recommended for more information and discussion. Since individual online resources require constant update and maintenance, sadly these resources are not available anymore. The learning curve to be able to code this system has become steeper due to the lack of these resources.

The PhD dissertation of A. Kirchner [25] has code snippets in the annex section which were promptly coded and tested, but with results that did not correspond to the expected values. This annex would have benefited from commentary. But mostly, this dissertation was not easily available from the references alone. The University of Cologne's webpage had to be searched in order to find these code snippets. After these resources were worked with, with little success, correspondence was exchanged with Dr. Schadschneider and Dr. Frank Mueller. After these helpful comments and corrections, the model was successfully implemented.

Due to the lack of discussion forums or raw code to analyze, which is a very important information since changes in algorithms cause big result differences, an open discussion and open code would be beneficial to this study. In order to avoid such difficulties for future students interested in starting their research in this branch of study, a documented repository has been created. This repository includes all previous versions of the code, as well as a wiki which will, hopefully, continue to be expanded. Coded implementations of decay and diffusion are exemplified and could prove useful for someone else's future research. This is, in my consideration, the most considerable contribution of this project. Open-source code documents mistakes, comments and how variations will affect the software. Science must be open-source, since results must be able to be replicated, and well documented.

`https://github.com/Silvia-exe/Cellular_Automata_Pedestrians`

7 Conclusion and Future Work Recommendations

We have proposed a new cellular automata model based on Kirchner et al Bionics-Inspired Floor Field model (2002). Firstly, Kirchner et al. results have been replicated using the same parameters as stated. Qualitatively, we have found that this thesis implementation of Kirchner's model will showcase the same key behaviors. Such behaviors include the radial movement of empty spaces from the door to the edges of the semi-circle formed around it. The implemented model also showcased the non-monotonic evacuation minimum for specific values of $k_{\mathcal{D}}$ and $k_{\mathcal{S}}$ There are quantitative differences between results, which have been blamed upon potential differences in the conflict resolution algorithm implemented or the dynamic field dynamics. Kirchner's regimes have been expanded upon and defined as different states of the system, which will be used moving forward. From this, it is concluded that the Optimal Regime, or the specific conditions where dynamic field coupling will help with faster evacuation times, is a very parameter-sensitive regime. In most cases, it is generally accepted that coupling to the dynamic field will result in adding noise to pedestrian movements thus increasing evacuation times.

Afterwards, the pedestrian population has been divided into two groups, each with different pairs of sensitivity parameters. This was aimed at simulating heterogeneous crowds, in which pedestrians will have different degrees of knowledge of the room's geometry and different degrees of attraction to high-flow regions. The density of pedestrians in the least-knowledgeable group of the population has been found to be highly correlated with higher evacuation times. This is due to the addition of the higher values of $k_{\mathcal{D}}$ adding extra non-useful information which confuses pedestrians into longer evacuation times. Additionally, in the specific configuration of pedestrians in the Ordered and Disordered regime, when pedestrians members of the Ordered evacuate fully, leaving behind pedestrians of the Disordered group, the latter ones will be more prone to create a random walk. This is due to the dynamic field decaying and leaving no useful information for their escape, finally escaping by mere chance. It is concluded that this model will be able to simulate high-stress scenarios by populating the room with a group with low values of $k_{\mathcal{S}}$ while keeping some pedestrians with $k_{\mathcal{D}}$ lower.

Dividing pedestrians into only two groups is also an oversimplification of an evacuation process, so the next possible step would be to divide pedestrians in N, differently populated groups each with different pairs of sensitivity parameters. It is also considered that, regardless of how little knowledge a pedestrian may have of the room, the position of the door will be apparent after visual confirmation of the door has been attained. Thus, after a pedestrian has attained certain proximity to the door, the attraction to it will increase and the now knowledgeable pedestrian will try to approach it. Thus, when approaching to a certain radius around the door, the $k_{\mathcal{S}}$ of the pedestrian will increase. Then, another future work proposal would be a sort of vision radius around the door, in which when pedestrians enter this radius would be now bonded to the door.

Further research on how the geometry of the room may impact on evacuation times, with focus in obstacles in close vicinity of the door is recommended. It is noted that, if inner walls, obstacles and/or furniture is to be modeled, the static field $\mathcal{S}$ may have to be defined differently to have lower values in regions where there are obstacles present. An example could be using the Manhattan metric.

More in focus with the computational side of the model, new research has showcased that GPU processing of cellular automata programs may decrease computing times. There are also some interesting results in 2 dimensional cellular automata [26]. An overlap in this new processing technique with pedestrian models may increment efficiency, allowing for increasingly complex scenarios. It is finally recommended that any further work must be done with an open-source initiative, documenting all code and leaving it free to the public to experiment with, since this research branch would greatly benefit from additions. In this specific thesis' coded implementation, the Object Oriented focus will make any contribution easier to implement thanks to its modular approach.

A Appendix: Construction of the Static Floor Field

The Static Floor Field's values $\mathcal{S}(i, j)$ for simple geometry such as the one worked in this paper (a rectangular room with no inner walls) uses a simple metric, but is is noted that the Manhattan metric is used for complex inner geometries. What follows now is the coded implementation of the static field constructor algorithm. This code and all its dependents is found in this thesis' repository found in the section 6.

```
/*Calculates the furthest away cell from every door*/
void floorPed::calcDL() {
 std::vector<int> d(door.size());
 for (int i = 0; i < x; i++) {
  for (int j = 0; j < y; j++) {
   for (int k = 0; k < door.size(); k++) {
    d[k] = sqrt(((door[k][0] - i) * (door[k][0] - i)) + ((door[k][1] - j) *
        (door[k][1] - j)));
    if (d[k] > d_L[k]) {
     d_L[k] = d[k];
    }
   }
  }
```

```
  }
}

/*Calculates the value of the static field for every door*/
void floorPed::calcStatF() {
  for (int i = 0; i < x; i++) {
    for (int j = 0; j < y; j++) {
      for (int k = 0; k < door.size(); k++) {
        statFieldVect[k][i][j] = d_L[k] - sqrt((door[k][0] - i) * (door[k][0] - i) +
             (door[k][1] - j) * (door[k][1] - j));
      }
    }
  }
}

/*Sets and calculates the final static field of the floor*/
void floorPed::statFieldInit() {
  calcDL();
  calcStatF();
  if (door.size() == 1) {
    statField = statFieldVect[0];
  }
  else {
    for (int i = 0; i < x; i++) {
      for (int j = 0; j < y; j++) {
        for (int k = 0; k < door.size(); k++) {
          if (statField[i][j] < statFieldVect[k][i][j]) {
            statField[i][j] = statFieldVect[k][i][j];

          }
        }
      }
    }
  }
}
```

B Appendix: Details on the Decay and Diffusion of the Dynamic Floor Field

The specific algorithm is shown as follows and it is also present in the repository.

This next logic will occur for every cell in the Dynamic Field $\mathcal{D}$.

1. The dynamic field cell starts with k steps.
2. k steps will have a chance of initial decay. k times a random number is generated. If this random number is less or equal to the decay parameter δ, we decrease the cell's step value by one. The number of steps that have decayed is now l.
3. $k - 1$ steps are left in the cell. These steps have now a chance of diffusion. $k - l$ times a random number is generated. If this random number is less or equal to the diffusion parameter α, we decrease the cell's step value by one. Then, $k - l$ times we will choose a random neighbor of the cell and increase the neighbor's value by one. The number of diffused steps is m.
4. There are now $k - l - m$ steps left in the cell. We move to the next $\mathcal{D}$ cell.

The explicit code is as follows:

```
/*Updates the dynamic field. With the use of a random number, it will decide if the
    dynamic field cell will decay or diffuse.
Diffusion is defined as increasing one of its neighbors value by one while diminishing
    the original cell's value.*/
void floorPed::dynamicDecay() {
 int difI;
 bool passed = false;
 int dynMagn = 0;
 /*Runs the dynamic decay for all cells in the floor. Will not run on walls to avoid
     bleeding of the dynamic field in walls cells to the floor cells. Since it will
     not run on walls, it is probable it wont run on doors.*/
 for (int i = 1; i < x - 1; i++) {
  for (int j = 1; j < y - 1; j++) {
   dynMagn = dynField[i][j];
   for (int l = 0; l < dynMagn; l++) {
    if (getRandom01() <= delta) {
     dynField[i][j] -= 1;
    }
   }
```

```
    dynMagn = dynField[i][j];
    for (int m = 0; m < dynMagn; m++) {
      if (getRandom01() <= alpha) {
        dynField[i][j] -= 1;
        difI = 1 + getRandomInt(0, 2) * (-2);
        if (getRandomInt(0, 2) == 0) {
          auxDynField[i + difI][j] += 1;
        }
        else {
          auxDynField[i][j + difI] += 1;
        }
      }
    }
  }
}
```

It is noted that, while implementing the dynamic field's decay, two issues came forward. Firstly, the decay and diffusion of the door's $\mathcal{D}$. This is important, since if left unchecked, the dynamic field's value for the door cell will increase to extremely high values. This caused an issue since, in the diffusion update, the cell chosen to be diffused upon, the neighbor, could be an uninitialized cell. Two solutions could be implemented. One, make the door an object and make the allowed neighbors an object variable. The one implemented in this thesis was a simple try...catch. The random door neighbor is chosen. Then, it is checked to exist. If it does, the diffusion is done. If not, a new neighbor is chosen. It is also noted that it is not recommended to run the dynamic field update to cells noted as walls since this behavior of diffusion to non-existant cells will become a major issue and any of the proposed fixes would increase computing time.

Secondly, the dynamic field's diffusion needs to be done via an auxiliary dynamic field. This is due to the diffusion's contribution to neighboring cells. If we increase the magnitude of a neighbors dynamic field via the diffusion dynamic, we cannot take this new boson into consideration for this neighbor's decay and diffusion. This is due to the necessity of a parallel update. We need to imagine and force all cells to update at the same time. This would mean that new contributions could not be taken into consideration. This is observed in the code snippet in this same annex. All dependants and comments can be found in this thesis repository found at numbered line **??**.

C Appendix: On the Probabilistic Methods used for Decision Making

C.1 On the Choosing Mechanism of Pedestrians

A probabilistic method is used in order for the pedestrian to ”decide” where their next desired move will be. When this is done, it has an stochastic method attached to it. The pedestrian will have five different transition probabilities.

North	West	Center	East	South
p(i, j-1)	p(i-1, j)	p(i, j)	p(i+1, j)	p(i, j+1)

Table 5: Array showing the five transition probabilities of a pedestrian

These probabilities are normalized so that the sum of them will always be one. In each update, a direction is chosen at random. Then, a random number between zero and one is calculated. The randomly chosen transition probability is compared to the newly created random number. If the random number is less or equal to the probability, then the pedestrian chooses the cell as a desired move. If the check is not passed, a new random cell is chosen, a new random number is calculated, and the process repeats. This may cause that, by mere chance, a cell with a relatively small transition probability will be chosen as a desired cell. This is an expected in-model result and emulates the non-deterministic behavior of individual pedestrians. The coded implementation can be seen in this annex' following snippet.

```
/*Function will select a random neighbor. This random neighbor's transition
    probability will be compared to a random number between 0 and 1. If the random
    number is lower or equal to the transition probability, then that cell is chosen
    as a desired move. If not, another random neighbor is chosen and the process
    repeats. This may cause cells with low transition probability to be chosen as a
    desired move. This accounts for human randomness.*/
int pedestrian::chooseDesiredMove() {
 double chooseCellRand = randomInt(0, 5);
 double comparison = randomNumber01(5);
 double tempProb = probVec[chooseCellRand];
 bool hasPedChosen = false;

 while (hasPedChosen == false) {
  if (comparison <= tempProb) {
   hasPedChosen = true;
   return chooseCellRand;
  }
  else {
```

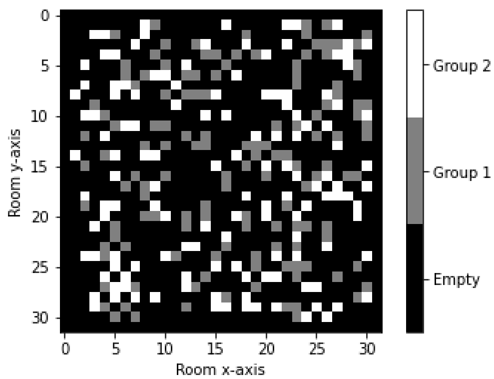
```
      chooseCellRand = randomInt(0, 5);
      comparison = randomNumber01(5);
      tempProb = probVec[chooseCellRand];
    }
  }
}
```

C.2 On the Conflict Resolution Between Pedestrians

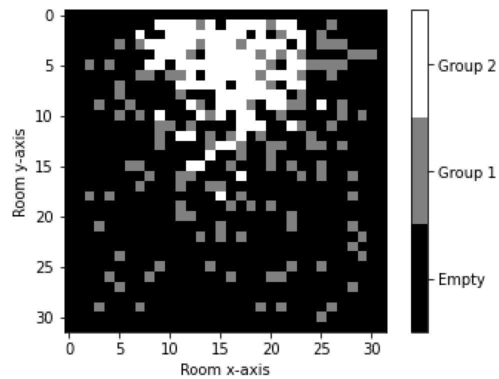
Firstly, it is noted that there exist at least two different algorithms for pedestrian choosing. In Kirchner et al. [4] there is the explanation of the creation of relative probabilities. A cell can be desired by zero until four pedestrians. When more than one pedestrian desires to move to a cell, a conflict arises. These conflicted pedestrians all have a calculated transition probability to move to the cell. In order to take this into consideration, relative transition probabilities are calculated and the decision process is made taken these new probabilities into consideration.

```
int pedestrian::chooseDesiredMove() {
  double chooseCellRand = randomInt(0, 5);
  double comparison = randomNumber01(5);
  double tempProb = probVec[chooseCellRand];
  bool hasPedChosen = false;

  while (hasPedChosen == false) {
    if (comparison <= tempProb) {
      hasPedChosen = true;
      return chooseCellRand;
    }
    else {
      chooseCellRand = randomInt(0, 5);
      comparison = randomNumber01(5);
      tempProb = probVec[chooseCellRand];
    }
  }

}
```

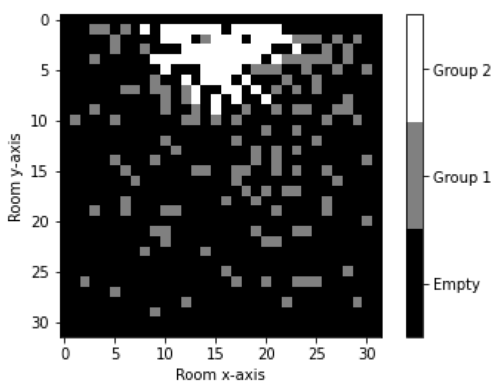
D Appendix D: Extra Figures



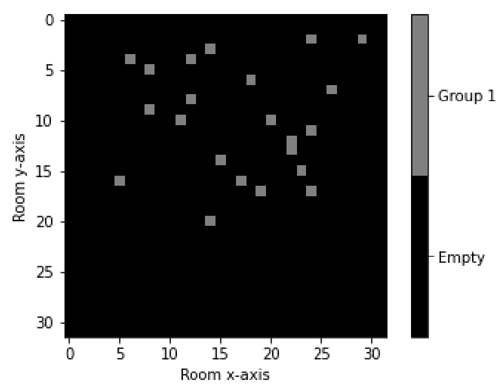
(a) Initial movement configuration for a 50/50 Group configuration between pedestrians in the Ordered (group 2) and Disordered Regime (group 1).



(b) Mid configuration. The pedestrians of group 1 are less aware of the door than pedestrians in group 2.



(c) Movement 260 of the evacuation process.



(d) Movement 5000 of the simulation where the members of group 1 are the only left.

Figure 18: Typical movements for a 50/50 configuration of a GSP FFCA model where pedestrians of group 1 are in an Disordered Regime and group 1 is in the Ordered Regime.

Acknowledgements and Thanks

I would like to give credit to Dr. Noureddine Lakouari and Dr. Julio César Pérez Sansalvador, for constantly giving feedback and for introducing me to the topic of traffic and pedestrian dynamics. To my thesis supervisor Dr. Miguel Ángel Ocaña Bribiesca for the close supervision of this thesis' progress which allowed me to constantly produce results and keep me on track.

We also acknowledge and deeply thank the helpful correspondence of Dr. Andreas Schadschneider and Dr. Frank Müller, without which this thesis' implementation would not have been finished.

Adam Gabriel Sobol, student from Universitetet i Oslo, for his useful constant feedback, for his irreplaceable correction of algorithms and his contributions to the project's repository for a faster, better graphical representation of the models. Thank you. My friends, Theodore, Michael, Lise and Bernhard for constructive criticism and comments, thank you.

Finally, I would like to thank my close family for their eternal patience and support during my whole studies. And F. D. C. Willard for constant inspiration.

References

[1] Andreas Schadschneider, Hubert Klüpfel, Tobias Kretz, Christian Rogsch, and Armin Seyfried. Fundamentals of pedestrian and evacuation dynamics. *Multi-Agent Systems for Traffic and Transportation Engineering*, 1:124–154, 2009.

[2] Roger L. Hughes. The flow of human crowds. *Annual Review Of Fluid Mechanics*, 35(1):169–182, 2003.

[3] Michael Seitz, Felix Dietrich, Gerta Köster, and Hans-Joachim Bungartz. The superposition principle: A conceptual perspective on pedestrian stream simulations. *Collective Dynamics*, 1, 03 2016.

[4] Ansgar Kirchner and Andreas Schadschneider. Simulation of evacuation processes using a bionics-inspired cellular automaton model for pedestrian dynamics. *Physica A: Statistical Mechanics and its Applications*, 312(1-2):260–276, 2002.

[5] World bank, urban development. https://www.worldbank.org/en/topic/urbandevelopment/, Oct 2022.

[6] Dirk Helbing. Empirical traffic data and their implications for traffic modeling. *Physical review. E, Statistical physics, plasmas, fluids, and related interdisciplinary topics*, 55, 06 1998.

[7] D Chowdhury. Statistical physics of vehicular traffic and some related systems. *Physics Reports*, 329(4-6):199–329, 2000.

[8] Dirk Helbing. Traffic and related self-driven many-particle systems. *Reviews of Modern Physics*, 73(4):1067–1141, 2001.

[9] Frank Müller, Oliver Wohak, and Andreas Schadschneider. Study of influence of groups on evacuation dynamics using a cellular automaton model. *Transportation Research Procedia*, 2:168–176, 2014.

[10] Gunter Barwolff, Thomas Slawig, Hartmut Schwandt, Theodore E. Simos, George Psihoyios, and Ch. Tsitouras. Modeling of pedestrian flows using hybrid models of euler equations and dynamical systems. *AIP Conference Proceedings*, 2007.

[11] Hartmut Schwandt, Stefan Berres, Theodore E. Simos, George Psihoyios, Ch. Tsitouras, and Zacharias Anastassi. A simulation model for two-phase pedestrian flow. *AIP Conference Proceedings*, 2011.

[12] Günter Bärwolff, Minjie Chen, Frank Huth, Gregor Lämmel, Kai Nagel, Matthias Plaue, and Hartmut Schwandt. Methods for modeling and simulation of multi-destination pedestrian crowds. *Pedestrian and Evacuation Dynamics 2012*, page 775–788, 2013.

[13] P.G. Gipps and B. Marksjo. A micro-simulation model for pedestrian flows. *Mathematics and Computers in Simulation*, 27:95–105., 1985.

[14] V.J. Blue and J. L. Adler. Emergent fundamental pedestrian flows from cellular automata microsimulation. *Transportation Research Record*, 1644:29–36, 1998.

[15] S Okazaki. A study of pedestrian movement in architectural space, part 1: Pedestrian movement by the application on of magnetic models. *Transportation Research Record*, 283:111–119, 1979a.

[16] Dirk Helbing and Péter Molnár. Social force model for pedestrian dynamics. *Physical Review E*, 51(5):4282–4286, 1995.

[17] Stefan Seer, Christian Rudloff, Thomas Matyus, and Norbert Brändle. Validating social force based models with comprehensive real world motion data. *Transportation Research Procedia*, 2:724–732, 2014.

[18] Schadschneider A. Zittartz J. Burstedde C., Klauck K. Simulation of pedestrian dynamics using a two-dimensional cellular automaton. *Physica A: Statistical Mechanics And Its Applications*, 295(3-4):507–525, 2001.

[19] Stephen Wolfram. Statistical mechanics of cellular automata. *Reviews of Modern Physics*, 55(3):601–644, 1983.

[20] Martin Gardner. Mathematical games. *Scientific American*, 223(4):120–123, 1970.

[21] Eric W. Weisstein. Moore neighborhood. https://mathworld.wolfram.com/MooreNeighborhood.html, 2003.

[22] Ulrich Weidmann. Transporttechnik der fussgänger. transporttechnische eigenschaften des fussgängerverkehrs, literaturauswertung. Technical report, Zürich, 1993-03.

[23] Kitao Abe. *Panikku no Ningen kagaku*. Brain Pub. Co., 1986.

[24] Cornelia Krüchten, Frank Müller, Anton Svachiy, Oliver Wohak, and Andreas Schadschneider. Empirical study of the influence of social groups in evacuation scenarios. 07 2016.

[25] Ansgar Kirchner. *Modellierung und statistische Physik biologischer und sozialer Systeme*. PhD thesis, University of Cologne, 2002.

[26] Daniel Cagigas-Muñiz, Fernando Diaz-del Rio, Jose Luis Sevillano-Ramos, and Jose-Luis Guisado-Lizar. Efficient simulation execution of cellular automata on gpu. *Simulation Modelling Practice and Theory*, 118:102519, 2022.