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Bachelor Thesis

Cellular automata modeling for pedestrian dynamics

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Contents

1 Motivation

The Loveparade 2010 in Duisburg with 21 dead and 541 injured demonstrated again how difficult it is to control and predict the dynamics of a large number of pedestrians, especially if panic appears and dominates the reactions of a crowd. One reason for this tragedy were mistakes in the planning phase for this event and a combination of events leading to the development of local panic. Especially in evacuation szenarios one needs to know the routes of the pedestrians to avoid jams and potential injuries. Many accidents where crowds of pedestrians were involved, happened because of planning mistakes and not because of mass panic. An overview about recent crowd accidents can be found in [1]. The physical pressure produced by bottlenecks in the mass dynamics was often the reason for injuries. A crowd moving into one direction may be hindered in motion due to an obstacle or a bottleneck so that a jam is triggered. At the same time, the following pedestrians keep their velocity and exert pressure on the pedestrians in the jam with smaller velocities. A local panic behaviour appears like at the Loveparade 2010, where only near the ramp between the access tubes to the event terrain panic was observed [2].

The exact knowledge of pedestrian behaviour plays an essential role in the planning of large constructions or for events, where high densities of pedestrians are expected. Experiments with many people are expensive and simulating experimentally stress situations like crowd disasters is almost impossible. Therefore, analysis of former crowd disasters is one way to try to avoid them in future. In addition, pedestrian dynamics is simulated with computer models, accounting within such models for empirical observations. One promising approach followed the last decades is the use of cellular automata models, instead of simulating the dynamics of individuals in so-called agent-based models.

At the beginning the basics of pedestrian dynamics will be presented and self-organizing phenomena in crowds will be explained. Afterwards, an overview about cellular automata and their application to pedestrian dynamics will be given. The algorithms used in this thesis will be expalined and validated. The validated model will be applied to different scenarios trying to discuss the influence and importance of panic for crowd dynamics. Finally, the work will be summarized.

2 Pedestrian dynamics

To simulate pedestrian dynamics it is necassary to charaterize the important parameters and behaviours. Here, both individual as well as crowd behaviour are important to know. This will be the topic of this chapter.

2.1 Basics of individual pedestrian dynamics

In general one must consider pedestrians as individuals with different targets. If several pedestrians have the same target they may try to reach it following different routes. Every pedestrian has an individual velocity, however this is strongly influenced by interactions with others. These interactions can reduce this velocity or even stop completely the movement, e.g. in jams. In the following, the major properties of pedestrian dynamics will be shortly summarized.

2.1.1 Route choice

Individual pedestrians try to minimze their effort to reach their target [3]. Detours or even movements against the prefered direction are avoided. If the target is not reachable directly, the pedestrians choose a series of intermediate targets, for which they aim straight for [3]. Therefore, the route of pedestrians can be approximated by a polygon [4].

Although pedestrians tend to use existing routes, trails between existing routes can be formed in addition as shortcuts, "they represent a compromise between the shortest possible distance and using already existing ways" [5]. An example is shown in Fig. 2.1.

Figure 2.1: Formation of trails at the campus of the university of Stuttgart [5]

2.1.2 Velocity distribution

Analysing the statistical properties of pedestrian dynamics one can describe the favourite velocity of individual pedestrians as Gaussian distributed [6]. The average of the Gaussian distribution is $1,34\frac{m}{s}$ with a standard deviation of $0,26\frac{m}{s}$. Additional dependencies exist also, like variations of this prefered speed with external influences. An example for this is the reduction of the average velocity with higher temperatures.

2.1.3 Space requirement

Pedestrians try to keep a safety distance to other pedestrians and to walls or obstacles. As described in [4] one has to distinguish between the space request in rest and during movement. The dynamic space request if a pedestrian is moving is significantly bigger than the space requested in rest. A larger safety distance is needed for moving pedestrians to be able to react to a sudden slow down of others intersecting the pathway and because of the pendulum motion of legs and arms during the movements.

At small pedestrian densities pedestrians may move with their individual favourite speed. With increasing density pedestrians experience stronger interactions with others and their speed decreases. Observations showed that there is no movement any more for densities larger than $5.4\frac{P}{m^2}$.

Looking at the horizontal projection of a pedestrian one gets a minimal space needed per pedestrian of $0.15m^2$ [4], [5]. This results in a maximal pedestrian density of $6.6\frac{P}{m^2}$.

2.2 Self organizing phenomena

Although pedestrians act on their own and independent, some interesting phenomena can be observed in crowds. In [5] these phenomena are described. A simulation model should reproduce as many of these effects as possible. Therefore, this work will use some of them as test cases for the simulation model developed here.

2.2.1 Lane Formation

Moving within a certain spatial corridor as shown in Fig. 2.2, pedestrians in crowds with different walking directions develop lanes. This is motivated by the fact, that such newly formed lanes reduce the collisions between pedestrians and allow for a higher flow.

Figure 2.2: Lane formation [4]

This effect gets even amplified if there are obstacles in the middle of the corridor. These obstacles seperate even better the movement of the different groups from each other. One example for this is the situation in undergrounds (Fig. 2.3).

If two flows of pedestrians cross the effect of striations can occur. Similar to the effect of lane formation in a corridor such striations minimize the interactions between pedestrians of different groups. In the case of striations this separation happens temporarily, whereas in the case of lanes this is done spatially.

Above a certain critcial density the lane forming collapses and groups of pedestrians with different targets get so close to each other that they are no longer able to move at all. This is called "freezing-by-heating".

Figure 2.3: Lane stabilization by an obstacle [4]

2.2.2 Oscillations at doors

At bottlenecks an oscillating like in Fig. 2.4 change of the flow direction is observed. Pedestrians waiting to get out of the door show an increasing impatience with time and an increasing pressure from this group builds up. If the pressure on one side of the door gets above a certain threshold this group will dominate the movement and the flow direction switches until the reversed situation sets in.

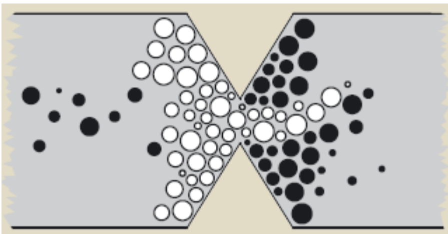


Figure 2.4: Oscillations at bottlenecks [4]

The frequency of the direction changes decreases with increasing length [5], because at longer bottlenecks the pedestrians have more diificulties to get an overview of the situation and tend to be more patient. The pressure within bottlenecks is getting larger and the pedestrians are blocked. This pressure is reduced with increasing size of the bottleneck and the pedestrians can pass easier.

3 Cellular Automata

In this section the concept of Cellular Automata and its possible application to the problem of pedestrian dynamics is introduced. Cellular automata divide the simulation domain into cells. These cells have to be regular, so that they form a regular grid. Every cell has one certain state value from a finite set of possible states.

The probably best known example for a cellular automaton is the "Game of life" by John Conway. A rectangular grid is considered. A cell has just two possible states, namely *dead* or *alive*. The change in the states are by the cells in the direct neighborhood. The time development from generation t to generation $t+1$ is determined by the following rules:

- A dead cell comes to life if it has exactly three living neighbors.
- Living cells with two or less living neighbors die because of solitude.
- Living cells with four or more living pedestrians die because of overpopulation.

The application fields of cellular automata are very wide spread, for example for the simulation of sand and snow dunes [7].

In this work, a cellular automata approach is followed to describe the dynamics of pedestrians. This is not strictly a classical cellular automata model, because the population number per cell is limited to one pedestrian at maximum. This means, that the movement of individual pedestrians is resolved in this approach and one gets close to agent-based models, just with simpler movement rules.

All pedestrians with the same target are marked as one group. This leads to the following states in a cell:

- cell is empty
- cell is an obstacle
- cell is occupied by a pedestrian of group 1

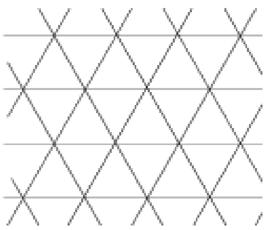
- cell is occupied by a pedestrian of group 2
- ...
- cell is occupied by a pedestrian of group N

Pedestrians can move only to empty cells. The update of the state variables, which represents the movement of the pedestrians, is done after each discrete timestep and depends on the states of the neighboring cells and on a set of rules for the time development $t \to t + 1$.

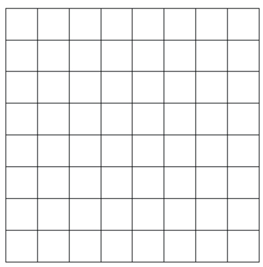
In the following a detailed description for one cell of a cellular automaton is given used to represent the dynamics of pedestrians following [4].

3.1 Grid structures

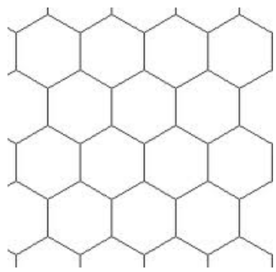
For practical purpose the grid has to be regular, what means that it is made only of one sort of regular polygons . Three possible types of grids exist:



triangular grid



rectangular grid



hexagonal grid

To decide now which grid structure is most appropriate for the simulation one has to look at the representation of pedestrians and walls or obstacles.

Pedestrians are often approximated by a circle which is nothing else than a polygon with an infinite number of edges. Therefore, it is not surprising that a hexagon is the best choice to represent pedestrians.

Also the arrangement of many pedestrians looks quite naturally within a hexagonal grid as shown in Fig. 3.1

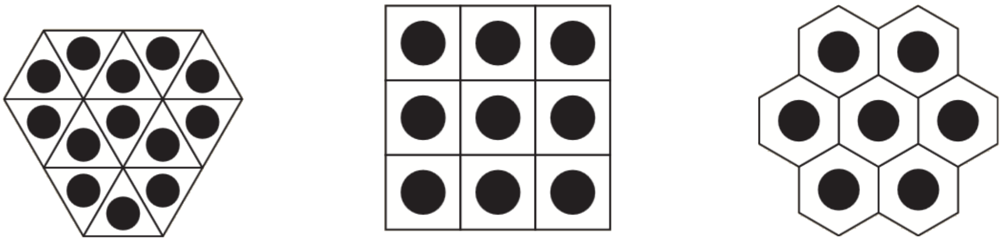


Figure 3.1: Distribution of pedestrians at high densities [4]

Walls or obstacles are again differently represented in these grids:

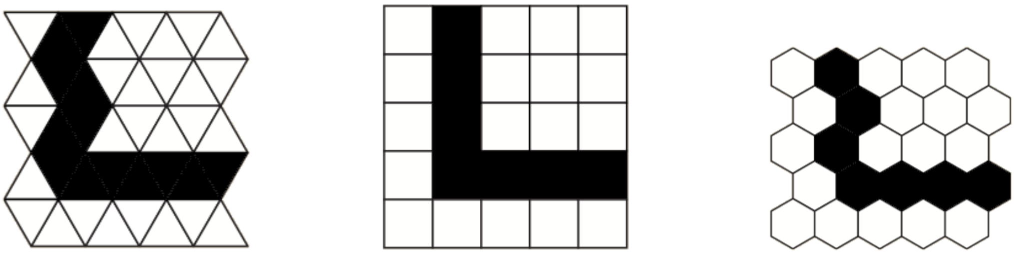


Figure 3.2: Depiction of walls with the different grid structures [4]

A rectangular grid is perfectly suited for walls, because most rooms are rectangular. Hexagonal and triangular grids are not appropriate to represent straight walls, but are more flexible for obstacles with complex shapes.

Both rectangular and hexagonal grids seem to be possible choices, wheras triangular grids have no advantage.

3.2 Neighborhood

For the change of the cell states in cellular automata only information from neighbouring cells are taken into account. In principle, any definition of neighborhood is possible. The only restriction is that the same definition has to be used for all cells.

Mostly one of the two following neighborhoods is used:

- Von-Neumann neighborhood: Just the neighboring cells which share one side with the basic cell are taken into account:

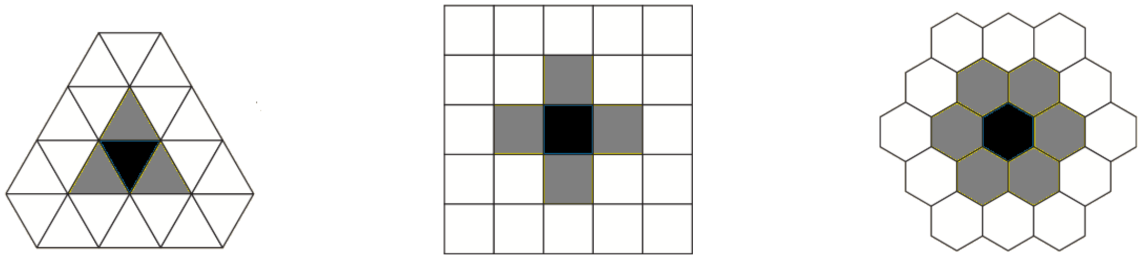


Figure 3.3: Von Neumann neighborhood in the different grid types [4]

- Moore neighborhood: All cells sharing at least one corner with the basic cell are considered as neighbors:

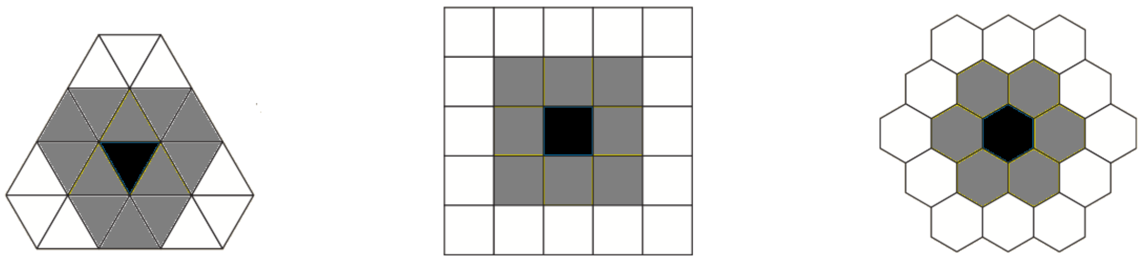


Figure 3.4: Moore neighborhood in the different grid types [4]

As one can see the neighborhood for the hexagonal grid is the same for both cases. The problem of forbidden moves by using the Moore-Neighborhood is mentioned in [4]. There may occur crossing moves using triangular and rectangular grids:

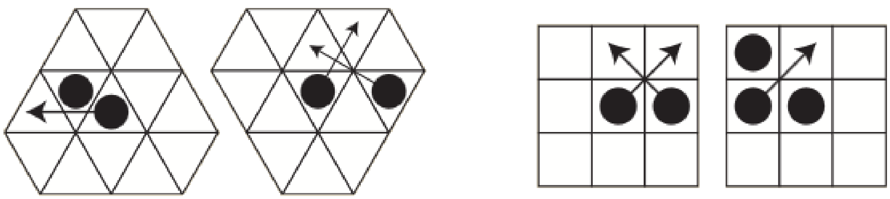


Figure 3.5: Forbidden moves by using the Moore neighborhood in triangular and rectangular grids [4]

Because of the isentropy of hexgonal grids there the problem does not appear. The triangular grid was never a good choice in all comparisons of grids. One can say that this grid structure is not suitable for the simulation of pedestrian dynamics and will no longer be discussed in this work. For a realistic representation of pedestrians hexagonal grids fit best. Their disadvantages are that they are not able to represent straight walls as good as rectangular grids and that they are quite difficult to implement. One alternative approach is the mapping to an rectangular grid [4]. The rectangular grid is not as good for representing pedestrians as the hexagonal grid, but it is very easy to implement. It was also already used succesfully before [8], [9]. Therefore, this thesis is also following this approach.

To complete the description of the cellular automata algorithm the update rules for the cells are needed.

3.3 Update rules

The update rules ensure a time development from timestep $t \to t+1$. Generally, one has to distinguish between parallel and sequential update rules.

By using parallel update rules the moves of all pedestrians are done simultaneously. In that case there might arise conflicts if two or more pedestrians want to enter the same target cell. Only the winner of the conflict is allowed to move, the others have to stay in their cells. In contrast to that movements of pedestrians proceed one by one by using sequential update rules. There are no conflicts, so a higher flow might be generated. Strictly seen the sequential update is not representing a classical Cellular Automaton, because all cells have to be treated equally.

Because conflicts are an important element of pedestrian dynamics only (stochastic) parallel update rules are considered in this thesis, but nethertheless in the following various implementation approaches for parallel and sequential update rules are presented as well. To give an overview a detailed description of the single update types is given in [10].

3.3.1 Stochastic parallel update

In general this class of update rules includes all parallel update rules based on statistical processes. In this thesis the following concept is used:

First every pedestrian has to choose which cell he wants to enter. For every pedestrian a transition matrix T is calculated. According to the von Neumann neighborhood a pedestrian is only allowed to move horizontally or vertically:

$$T = \begin{pmatrix} 0 & p_{10} & 0 \\ p_{01} & p_{11} & p_{21} \\ 0 & p_{12} & 0 \end{pmatrix}$$

How the elements of the transition matrix are calculated is discussed in section 4.2. The elements of T act as transition probabilities. Therefore, T must be normalized:

$$\sum_{i=0}^{2}\sum_{j=0}^{2} T_{ij} = 1$$

p_{11} is the probability for a pedestrian to stay in a cell. Now a random number is used to decide what is the prefered move. If two or more pedestrians want to enter the same target cell a conflict appears. To resolve the conflicts for every target cell a 3 x 3 collision matrix C is created to represent the direct neighborhood of the cell. If a pedestrian decide to enter a free cell, then the transmission probability of the pedestrian towards the free cell is saved as the element in the collision matrix of the free cell corresponding to the current location of the pedestrian. The sum over all elements of C can be unequal 1.

After all pedestrians determined which is their prefered move, the collision matrices are filled with the transition probabilities of the pedestrians who want to enter a cell. If two or more pedestrians want to enter the same cell a conflict arises. Based on the values of the collision matrix a random number is generated that decides which pedestrian wins the conflict and is allowed to execute his move. All other pedestrians have to stay in their current cell.

3.3.2 Deterministic parallel update

In difference to stochastic parallel update rules there are no random numbers are used in the update rules. This means, that the system is totally predictable for a given starting configuration. A possible definition of that kind of rules might be:

For all pedestrians:

1. Create transition matrix & normalize T.
2. Go through T: $T_{11} \to T_{12} \to ... \to T_{33}$.
3. The T_{ij} with the highest value is the prefered move, if there are more than one cell sharing the highest value the prefered move is that cell, where it appears first.
4. Save T_{ij} in the collision matrix C of the target cell.

For all collision matrices:

1. Get the highest value of C.
2. If there are more than one cell sharing the highest value the one where it appears first wins.
3. Execute step.

3.3.3 Ordered sequential update

In case of ordered seuqntial update rules a fixed order is given, which after the pedestrians move. Thereby the order has an influence on the development of the system. One possible implementation of this rules might be:

1. Go through the floor field F: $F_{11} \rightarrow F_{12} \rightarrow ... \rightarrow F_{RC}$ with R : number of rows and C : number of coloumns.
2. If F_{ij} is occupied by a pedestrian:
   - Create transition matrix & normalize T.
   - Choose per random number what is the prefered move. The elements of T act again as transition probabilities.
   - Execute step.

3.3.4 Shuffled sequential update

By using shuffled sequential update rules the order after that the pedestrians move is randomly choosen after every timestep. One can implement this as follows:

1. Save the coordinates of every pedestrian in a list
2. Do until the list is empty:
   - Draw a random number q between $1..N$ assuming there a N elements in the list.
   - Create transition matrix & normalize T for the pedestrian at position q in the list.
   - Choose per random number what is the prefered move. The elements of T act again as transition probabilities.
   - Execute step.
   - Remove element from list with position q.

4 Model

There are many approaches for describing crowd movements based on Cellular Automata. The model used here is based on [9]. In the following a rectangular grid and the von Neumann neighborhood is used. For a validation of the model, an evacuation situation with randomly distributed pedestrians that want to leave a room with only one exit door is considered.

A key idea for the model is to introduce complex interactions in the form of potential fields. The dominant drive for the movement of the pedestrians is the minimzation of the distance to the goal. This is represented numerically in a static potential field describing the metrics for the pedestrians and will be explained in detail in the next section. Afterwards, the infuence of long range effects triggered, e.g. by panic, will be included in the model using a dynamic potential field affecting the movement of the pedestrians.

4.1 Static floor field S

First one defines a static potential field S to determine the pedestrian dynamics. For that many definitions are possible. In this static field the influence of the ground, obstacles and the attraction by doors are taken into account. First, an approach as in [11] is used.

The value of the static field of the cell with coordinates (i, j) are given by the euclidic distance to the nearest exit:

$$\tilde{S}_{ij} = \min_{l} \sqrt{(x_{ij} - x_{E_l})^2 + (y_{ij} - y_{E_l})^2}$$

x_{E_l} and y_{E_l} are the coordinates of the l^{th} exit. In the next step the maximum value of $\tilde{S}_{ij}$ is computed:

$$m := \max_{ij} \tilde{S}_{ij}$$

The resulting static floor field S is now given through:

$$S_{ij} = m - \tilde{S}_{ij}$$

So the "field values increase with decreasing distance to an exit and is zero for the cell farthest away from the door" [11].

There are no obstacles considered in this definition of the static floor field. Because of that and because of the von Neumann neighborhood it is appropriate to use the manhattan distance metric. The distance between a point $\vec{p}_1 = (i, j)$ and the exit $\vec{p}_2 = (x_{E_l}, y_{E_l})$ is given by:

$$d = |x_{E_l} - x_1| + |x_{E_l} - y_1|$$

The value of a cell is equal to the minimal number of steps needed to reach the exit.

By implementing the Manhattan distance metric one has to consider that obstacles will enlarge the minimum number of needed steps, because one has to go around them. The implementation can be done following [8]:

1. The exit doors are assigned the value 0.

2. Set a counter $c = 0$.

3. Do until all cells are evaluated:
   - All vertical and horizontal adjacent cells of cells with value c if the adjacent cell is still unevaluated.
   - Increase the counter by 1.

After that the same procedure as before is done to insure that the field values increase with decreasing distance to the exit.

4.2 Friction

First one has to calculate all T probabilities. For that, the static floor field is used:

$$T_{ij} = N \cdot n_{ij} \cdot exp(k_S \cdot S_{ij})$$

With N as a normalization factor and k_S as a parameter to adjust the influence of the static floor field.

The pedestrians get a certain probability μ to stay in their cells in case of a conflict even if they are permitted to move. Now the evacuation time as a function of the parameter k_S is considered for different friction parameters μ, for a grid size of 63 x 63 and one exit door with a width of 1 in the middle of one wall. As mentioned in [12] k_S acts as an effective velocity towards the exit. For small k_S the pedestrians perform a random walk. For big k_S the transition probability towards the cell next to the door is much bigger than the others, so the pedestrians accumulate infront of the door. As a consequence more collisions appear and the flow of the pedestrians decreases ("Faster-is-slower effect"). This corresponds to the results for high friction paramters μ shown in Fig. 4.1.

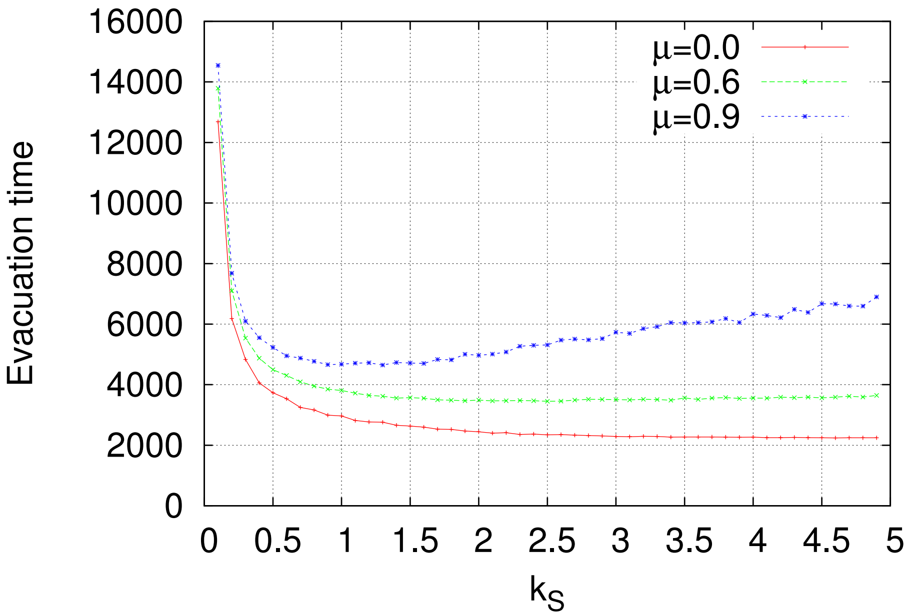


Figure 4.1: Evacuation time depending on k_S for various friction parameters μ

4.3 Dynamic floor field D

There is no interaction existing between the pedestrians except collisions and the effect that a pedestrian cannot access an occupied cell. To include interactions between pedestrians beyond this short range one can use an approach like in [9] and define a dynamic floor field D through which Pedestrians are affected by the traces of other pedestrians.

D is defined as follows:

At the beginning of the simulation all values of D are 0. Every pedestrian move affects the dynamic floor field D. If a pedestrian moves from cell (i, j) to another cell, D of the original cell is increased by one:

$$D_{ij} \rightarrow D_{ij} + 1$$

D is interpreted as a kind of "bosonic field" [9] and underlies effects of decay and diffusion. It decays with a probability δ and diffuses with a probability α to one of its neighbored cells. Further one can define a coupling constant k_D to adjust the influence of the dynamic floor field. Because the pedestrians also would be influenced by their own trace, the Boson created in the last step will be corrected such that this self-effect is taken out. Therefore, every pedestrian has its own individual dynamic floor field D [13].

In the here developed program the update of the dynamic field is done at the beginning of each timestep. The particle created in the last step already might has decayed or diffused. For small decay constants δ the trace of a pedestrian lasts longer. This makes it neccassary to correct out more particles than only the ones created in the last step.

The transition matrix is given through:

$$T_{ij} = N \cdot n_{ij} \cdot exp(k_S \cdot S_{ij} + k_D \cdot D_{ij})$$

To validate the code with cases from literature [9] one can test how the evacuation time changes for different k_D and α with $\delta = 0.3$ fixed.

Results are shown in Fig. 4.2 for a grid size of 63 x 63 and for only one exit door with a width of 1 in the middle of one wall.

The curve agrees qualitatively with [9]. Remaining differences originate probably from differences in the implementation of the update rules from the dynamic field, which are not well documented in the reference publication.

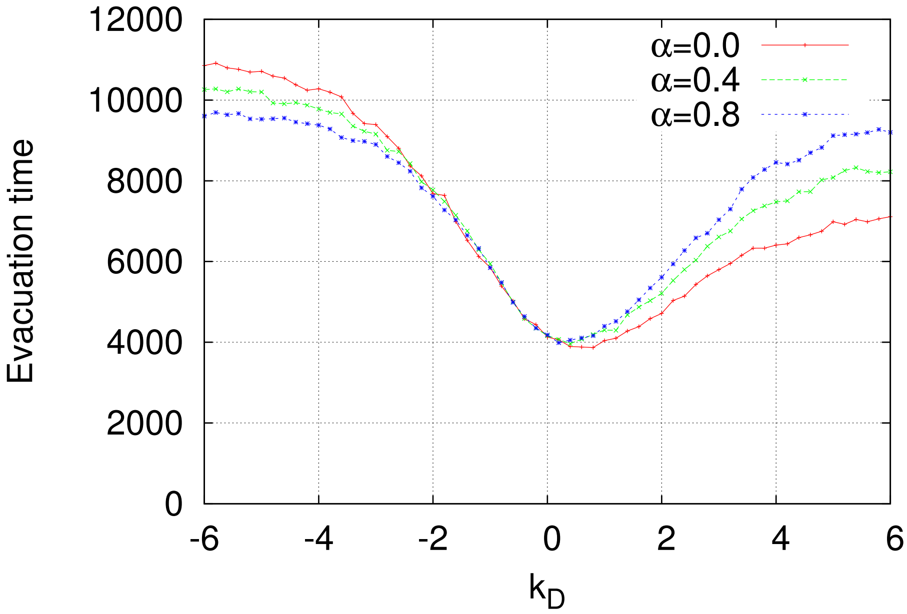


Figure 4.2: Evacuation time depending on k_D for various diffusion parameters α

4.4 Additional changes

4.4.1 Modification of k_S

As seen in [6] the velocity of the pedestrians is Gaussian distributed. With k_S as a kind of effective velocity towards the exit one can assume that every pedestrian has his own k_S. In the following k_S is chosen to be equally distributed in the interval $[k_{S_0} - \sigma, k_{S_0} + \sigma]$ with an additional parameter σ to adjust the spread of k_S. Now one can compare the evacuation time for different σ by $k_S = 1.0$, $k_D = 0.0$, all other parameters are as before.

The pedestrians with $k_S = k_{S_0} - \sigma$ determine the evacuation time. Because of the small effective velocity towards the exit they tend to perform a random walk, which enlarges the evacuation time as one can see in Fig. 4.3.

Of course this is not a real multispeed model, because the pedestrians are allowed to make only only one step per timestep. An possible implementation of a multi-speed model is described in [10].

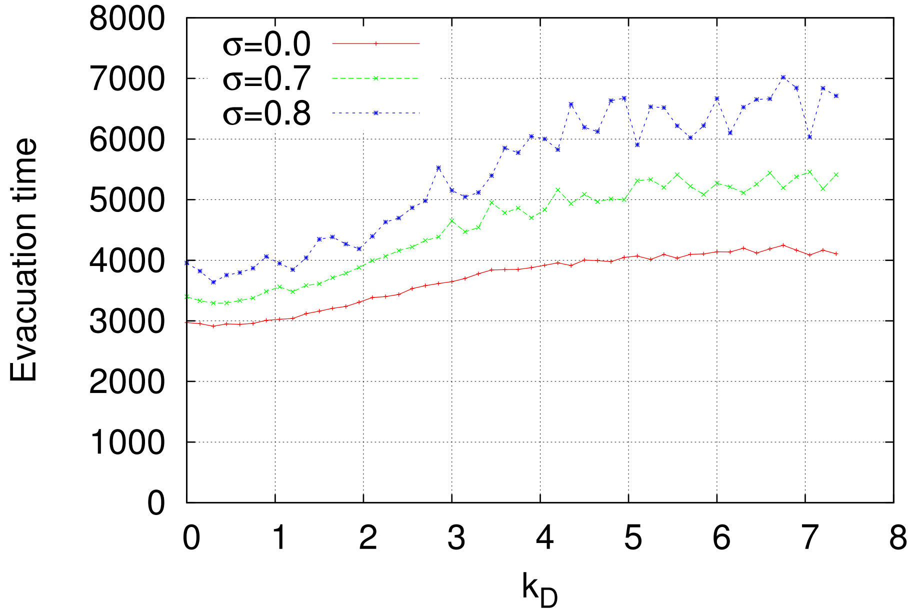


Figure 4.3: Evacuation time depending on k_D for various σ

4.4.2 Modification of the dynamic field coupling

Following [14] the coupling factor of the dynamic floor field can be interpreted as an indicator for the extent of the herding behaviour of pedestrians. In panic situations the influence of the dynamic floor field will dominate over the influence of the static field. As seen in [2] "panic" tends to occur in regions of jamming. Instead of a fixed static coupling the influence of the dynamic field will be different for every pedestrian. Pedestrians far away from a region of jamming will be less influenced by the dynamic floor field. k_D will act as a basic coupling parameter supplemented by an additional factor c_i. One can choose a similar approach as for the dynamic floor field:

1. Initially c_i is 0 for every single pedestrian.
2. Every collision increases c_i by one.
3. If a pedestrian is longer not involved in collisions, c_i shall decrease because of decay.
4. A pedestrian is in panic, if c_i is larger than a certain value P.
5. If a pedestrian is in panic he increases the c_i of pedestrians in the neighborhood by 1 at every iteration.

The transition matrix is now given as:

$$T_{ij} = N \cdot n_{ij} \cdot exp(k_S \cdot S_{ij} + (k_D + c_i) \cdot D_{ij})$$

Now one can investigate the influence of c_i on the evacuation time for densities ϱ with $P = 5$, $k_S = 0.4$, $\mu = 0.0$ fixed:

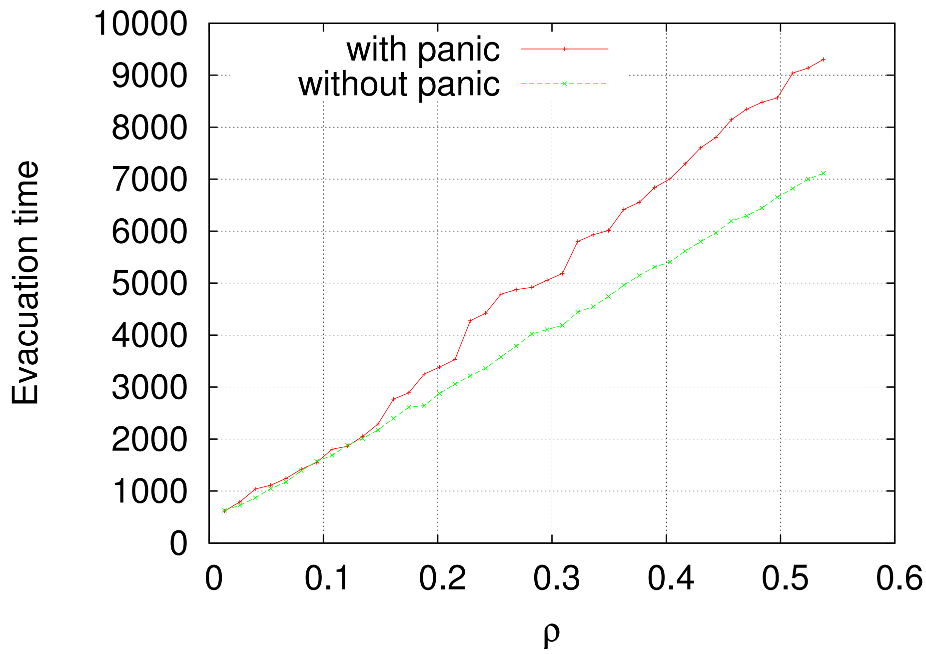


Figure 4.4: Evacuation time depending on the pedestrian density ϱ

As one can see in Fig. 4.4 the evacuation times are equal for low densities. With increasing density the amount of panic increases. As a consequence the evacuation time compared with the case without panic increases.

4.4.3 Modification of the static floor field S

In evacuation situations humans tend to use the door through which they entered a room [2]. This must be considered in the static floor field. For every pedestrian it is randomly chosen through which door one enters the room.

Therefore, a static field S_i for every exit is created. The resulting static floor field S is given by:

$$S = \sum a_i \cdot S_i$$

Note that every pedestrian may have his own set $\{a_i\}$, so every pedestrian is influenced by a different S.

The a_i are parameters to adjust the influence of the exits on the pedestrians.

Now one can investigate how the evacuation time changes for different densities ρ and for two cases:

1. The pedestrians aim only for the nearest exit. In that case all a_i are 0 except the one belonging to the nearest exit, so after every timestep the nearest exit must be computed for every pedestrian.

2. The pedestrians aim for the exit through which they entered the room. One can assume that the exits are equally distributed between the pedestrians.

Usually, the majority of the pedestrians chooses the main entrance. One can assume that 50% of the pedestrians shall take one entrance and the others are equally distributed on the remaining entrances. This yields for a grid size of 63 x 63, $k_S = 0.4$, $\mu = 0.4$, $k_D = 0.0$ and an exit in the middle of each wall:

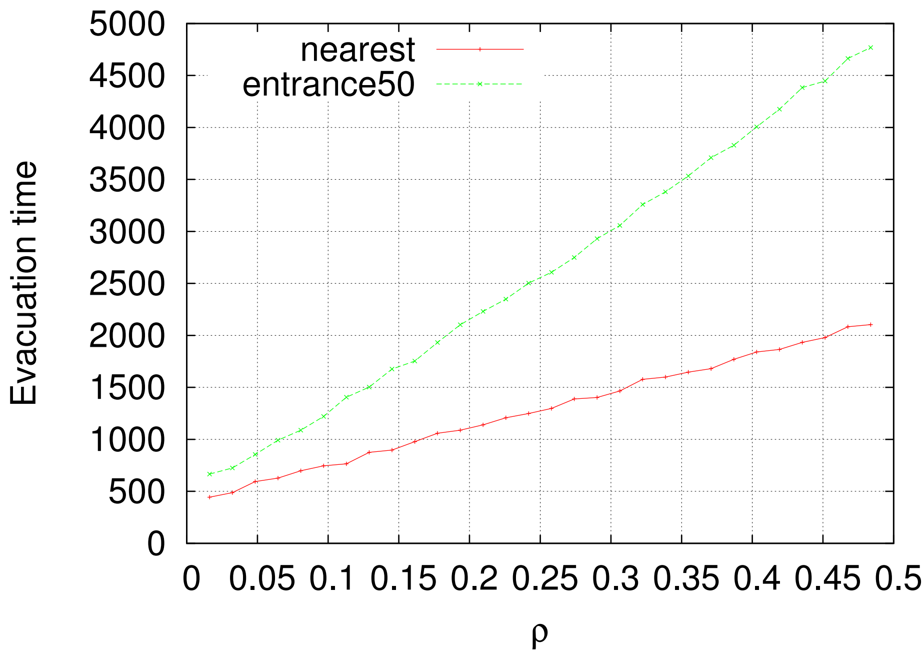


Figure 4.5: Evacuation time depending on the density

As one can see in Fig. 4.5 the evacuation time increases in the case that the majority of the pedestrians wants to leave the room through the main entrance. This must be considered in the evacuation plannings of buildings.

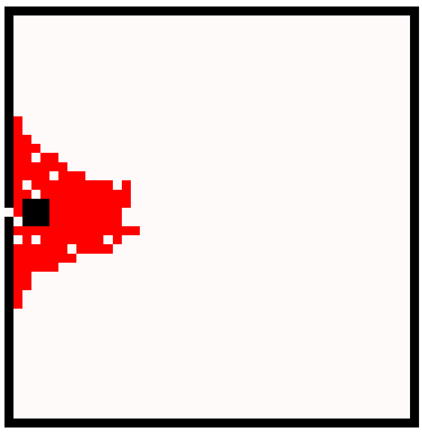
5 Applications

In chapter 4 the model for simulating pedestrian dynamics was described. In this part results of the model for typical applications are presented.

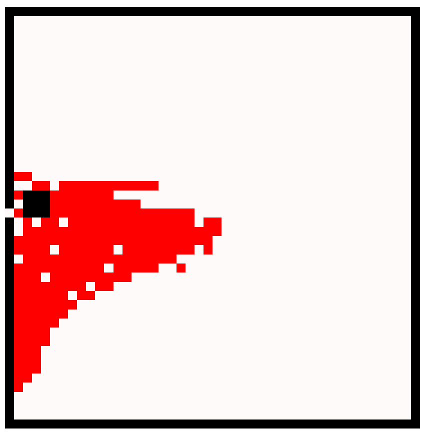
5.1 Obstacle in front of an exit

In the following the influence of an obstacle in front of an exit will be investigated. Naively one would expect, that obstacles increase the evacuation time, because pedestrians have to walk around them. As mentioned in [13], the obstacle acts like a "breakwater". As a consequence less conflicts occure and the pedestrian flow is higher than for a configuration without an obstacle. To consider the obstacles in the static field the manhattan distance metric, as in section 4.1 introduced, is used.

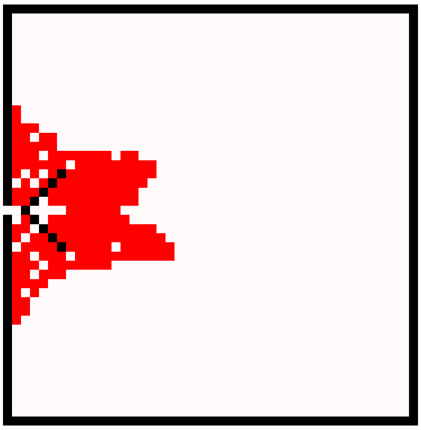
Different forms and locations of obstacles in front of the exit are studied:



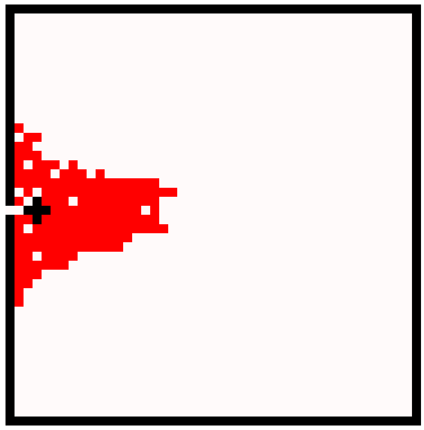
a) A 3x3 obstacle in front of the exit



b) A 3x3 obstacle in front of the exit shifted by one cell



c) Obstacle formed like an arrowhead



d) Obstacle to imitate a round pillar

For the different obstacles the evacuation time as a function of the friction parameter μ is shown in Fig. 5.1. The results are presented for $k_S = 5.0$, 1000 pedestrians, a grid size of 46 x 46 and $k_D = 0.0$. In case of $k_D = 0.0$ the simulation represents an ordered evacuation. The influence of the obstacles is only visible for high friction parameters μ.

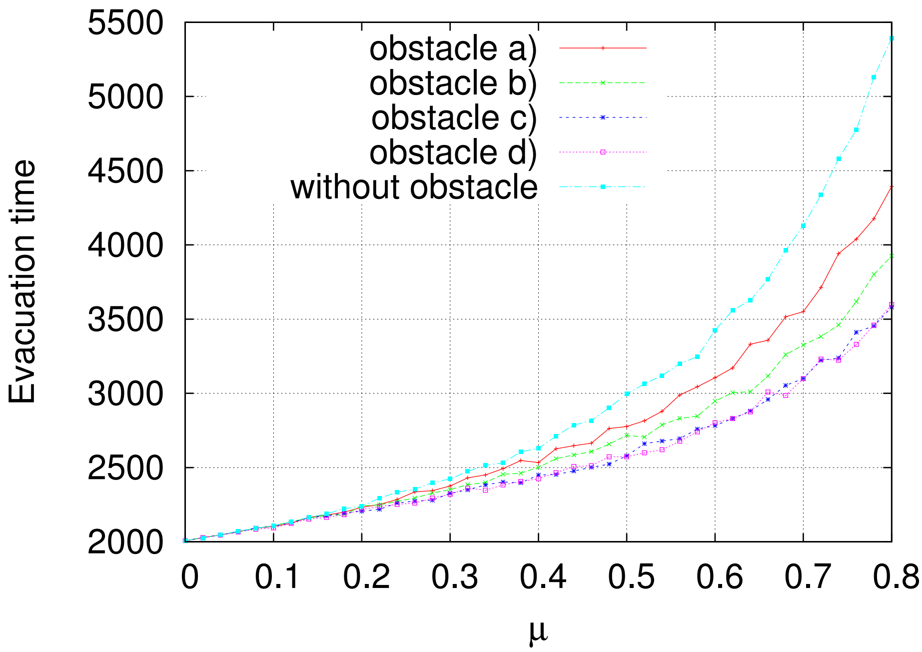


Figure 5.1: Evacuation time depending on μ for various forms of obstacles

The effect on the evacuation time by a pillar of 3 x 3 cells positioned one cell shifted away from the exit is stronger than for a pillar direct in front of the exit. Because of the shifting an asymmetry in the flow of the pedestrians around the obstacle occurs, so that more pedestrians take one side of the obstacle. In that case the number of collisions in front of the exit is stronger decreased than for a symmetric flow of pedestrians. Therefore, less friction in front of the exit occurs and the evacuation time decreases. Other obstacle forms with more complex geometries, e.g. with serrated forms of obstacles, can also be tested. In contrast to the simple expectation that a kind of funnel effect occurs reducing the evacuation time almost the same evacuation time is observed in the simulations. One can conclude that the parts of the arrowheaded obstacle has no influence.

In real evacuation situation panic may occur. Therefore, also the influence of the dynamic field has to be considered. Panic, or a stronger herding behaviour of the pedestrians, may be simulated by using high coupling parameters k_D of the dynamic field D to mimic panic. As one can see in Fig. 5.1 the differences in the evacuation times only occur in case of high friction parameters μ. Therefore, it is reasonable to investigate the dependence of the evacuation times on k_D for a large friction parameter $\mu = 0.8$. This is shown in Fig. 5.2. Also one can choose a high value of k_D and repeat the simulation shown in 5.1. The results for that case are shown in 5.3. One can see that also in panic situations the obstacles have a positive influence on the evacuation time. But in contrast to the ordered evacuation the form of the obstacles do not matter. By large k_D the attraction between the pedestrians is very strong. One can say the pedestrians "stick" together. This can be compared to a large viscosity, whereby the pedestrians just slowly get around the obstacle. Therefore, the detailed geometry of the obstacle has no influence anymore, but the existence of an obstacle regulating the outflow is always beneficial.

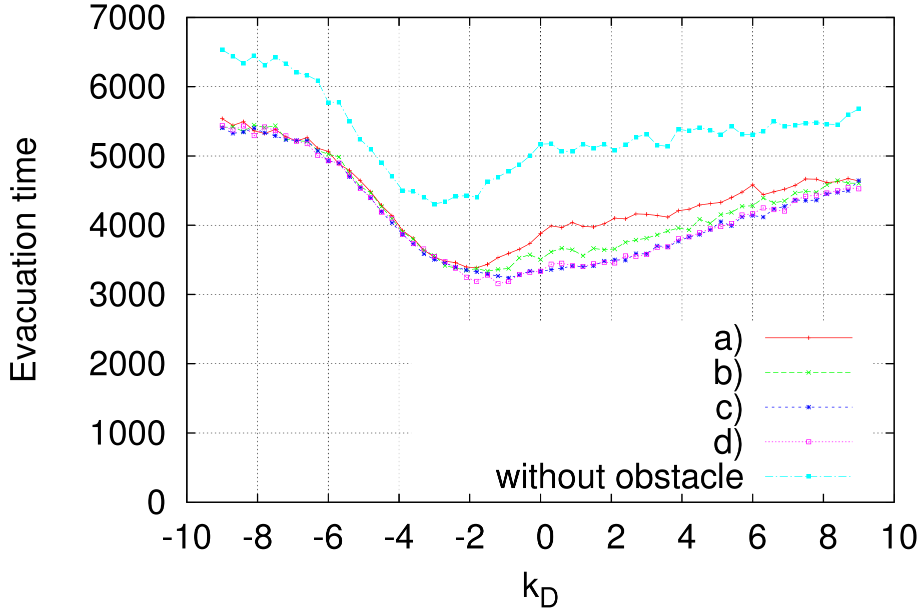


Figure 5.2: Evacuation time as a function of k_D for various forms of obstacles for $\mu = 0.8$

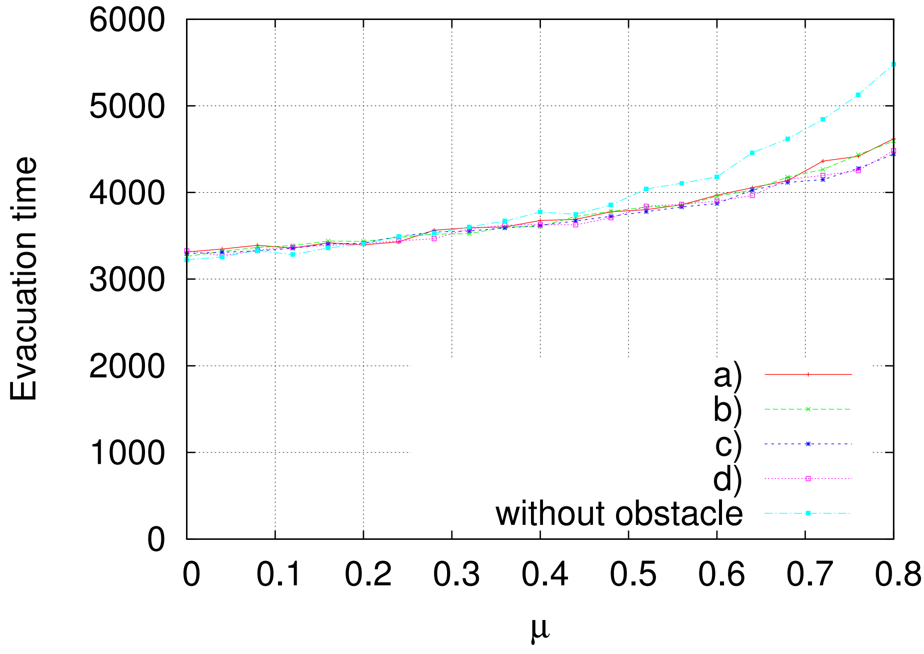


Figure 5.3: Evacuation time as a function of μ for various forms of obstacles and for $k_D = 8.0$

5.2 Long corridor

To test the lane formation a long corridor with two groups of pedestrians is considered. The groups of pedestrians move through the corridor in opposite directions. Initially, the pedestrians are distributed randomly as shown in Fig. 5.4. Pedestrians in blue move to the right while pedestrians in red move to the left.

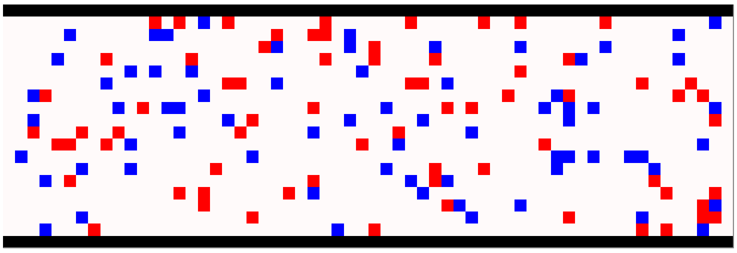


Figure 5.4: Initial distribution of the pedestrians

Because the groups move in opposite directions there is one static field for each group needed. The static fields are $S_1 = x$ for pedestrians moving to the right and $S_2 = x_{max} - x$ for the other group.

Pedestrians following other pedestrians of their group are involved in less collisions than pedestrians facing pedestrians moving in the opposite direction. Furthermore, pedestrians act attractive on pedestrians of their own group while they act repulsive on pedestrians of the other group.

The transition probabilities for group 1 are given by:

$$p_{ij} = N_1 \cdot exp(k_S \cdot S_1[i][j]) \cdot exp(k_D \cdot (D_1[i][j] - D_2[i][j]))$$

Analogous the transition probabilities for group 2 are:

$$p_{ij} = N_2 \cdot exp(k_S \cdot S_2[i][j]) \cdot exp(k_D \cdot (D_2[i][j] - D_1[i][j]))$$

To simulate a long corridor periodic boundary conditions for the entrance/exit of the corridor are used. If a pedestrian reaches the end of the corridor it re-appears on the opposite side of the corridor and is considered in the collision treatment.

Now one can investigate how the system behave for $k_S = 5.0$ and $k_D = 15.0$. In Fig. 5.5 one can see the formation of lanes, but the separation is rather incomplete.

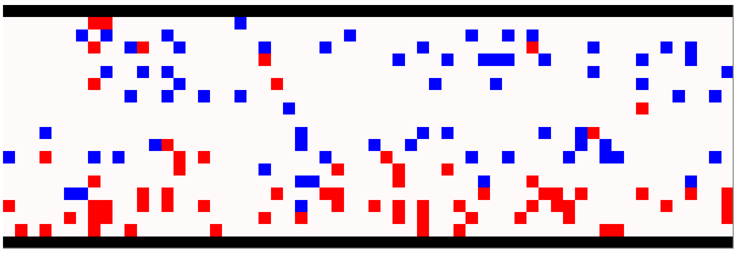


Figure 5.5: Lane formation

The simulation is repeated with a line of obstacles in the middle with enough space in between that. pedestrians are able to change the lanes.

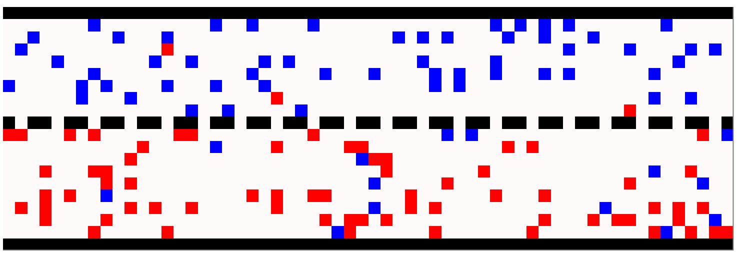


Figure 5.6: Lane stabilisation

As can be seen in Fig. 5.6 the effect of lane formation is amplified with a much better separation. This corresponds to the self organizing phenomena discussed in section 2.2.1.

6 Conclusion and outlook

Within this thesis a model for the simulation of pedestrian dynamics based on cellular automata with parallel update rules was implemented. The influence of the spatial structure on the pedestrians was taken into account by a static field S. A dynamic field D allows to introduce pedestrian interactions acting on longer ranges, particularly important to represent panic. Using a friction parameter μ to study effects of jamming the "faster is slower" effect could be observed. By increasing the relative strength of the dynamic field the herding behaviour of pedestrians gets more pronounced as observed in panic situations.

The influence of obstacles in front of an exit in evacuation szenarios was investigated. The results correspond to other works [15]. Phenomena like lane formation and lane stabilisation by obstacles could be reproduced successfully.

The model is still incomplete, because some other effects, like oscillations at bottlenecks, can not be reproduced. This needs a full agent-based approach resolving in more detail the movement of individual pedestrians and their interaction. Another example of a short-coming of the existing approach is the fact pedestrians only execute one move per timestep at maximum. Again, an agent-based model would not suffer from this problem. Approaches to extend a cellular automata model to a multi speed model are given in [10].

The biggest challenge for all models of pedestrian dynamics is the correct treatment of panic which requires knowledge of human sociology, human psychologically and quantative descriptions of forces on pedestrians in crowds. This complexity defines this area of research as a typical example where further progress will only be possible with an interdisciplinary approach.

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7 Ackknowledgments

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