Bionics-inspired cellular automaton model for pedestrian dynamics

Andreas Schadschneider

Institut für Theoretische Physik, Universität zu Köln, 50937 Köln, Germany

Abstract. We present a 2-dimensional cellular automaton model for the simulation of pedestrian dynamics. Inspired by the principles of chemotaxis the interactions between the pedestrians are mediated by a so-called *floor field*. This field has a similar effect as the chemical trace created e.g. by ants to guide other individuals to food places. In our case the floor field modifies the transition rates to neighbouring cells. It has its own dynamics (diffusion and decay) and can be changed by the motion of the pedestrians. This means that in our model pedestrians follow a virtual rather than a chemical trace as in the case of chemotaxis. The approach is extremely efficient and makes faster-than-real-time simulations of large crowds possible. Already the inclusion of only nearest-neighbour interactions allows to reproduce many of the collective effects and self-organization phenomena (lane formation, flow oscillations at doors etc.) encountered in pedestrian dynamics.

1 Introduction

Methods from physics have been successfully used for the investigation of vehicular traffic for a long time [1,2]. On the other hand, pedestrian dynamics has not been studied as extensively. Due to its generically two-dimensional nature, pedestrian motion is more difficult to describe in terms of simple models. However, many interesting collective effects and self-organization phenomena have been observed (see [2,3] for an overview and a comprehensive list of references):

- **Jamming**: At large densities various kinds of jamming phenomena occur, e.g. when many people try to leave a large room at the same time. This clogging effect is typical for a bottleneck situation. Other types of jamming occur in the case of counterflow where two groups of pedestrians mutually block each other. This happens typically at high densities and when it is not possible to turn around and move back, e.g. when the flow of people is large.
- **Lane formation**: In counterflow, i.e. two groups of people moving in opposite directions, a kind of spontaneous symmetry breaking occurs (see Sec. 4). The motion of the pedestrians can self-organize in such a way that (dynamically varying) lanes are formed where people move in just one direction [4]. In this way, strong interactions with oncoming pedestrians are reduced and a higher walking speed is possible.
- **Oscillations**: In counterflow at bottlenecks, e.g. doors, one can observe oscillatory changes of the direction of motion. Once a pedestrian is able to pass the bottleneck it becomes easier for others to follow him in the same direction

until somebody is able to pass (e.g. through a fluctuation) the bottleneck in the opposite direction.

- **Patterns at intersections**: At intersections various collective patterns of motion can be formed. A typical example are short-lived roundabouts which make the motion more efficient. Even if these are connected with small detours the formation of these patterns can be favourable since they allow for a "smoother" motion.
- **Panics**: In panic situations many counter-intuitive phenomena (e.g. "faster-is-slower" and "freezing-by-heating" effects [5]) can occur. For a thorough discussion we refer to [3,6,7] and references therein. Elsewhere in these proceedings we will study the dynamics of evacuation processes in more detail [8] (see also [7,9–11]).

In recent years, several models for the description of pedestrian dynamics have been suggested:

- **Social force models**: So far continuum models have been most successful in modelling pedestrian dynamics. An important example are the social force models (see e.g. [2,4] and references therein). Here pedestrians are treated as particles subject to long-ranged forces induced by the social behaviour of the individuals. This leads to (coupled) equations of motion similar to Newtonian mechanics. There are, however, important differences since, e.g., in general the third law ("actio = reactio") is not fulfilled.
- **Active walker models**: So-called active walker models [12,13] have been used to describe the formation of human or animal trails etc. Here the walker leaves a trace by modifying the underground on his path. This modification is real in the sense that it could be measured in principle. For trail formation, vegetation is destroyed by the walker and some animals (like ants) leave a chemical trace which can be detected by other animals.
- **Cellular automata**: Most cellular automata (CA) models for pedestrian dynamics proposed so far are rather simple [14–17] and can be considered as generalizations of the Biham-Middleton-Levine model for city traffic [18]. However, these models are not able to reproduce all the collective effects observed empirically. The same is true for more sophisticated discrete models, e.g. the one suggested by Gipps and Marksjös [19] or a disretized version of the social force model [20].

In [21,22] a new kind of CA model has been introduced which – despite its simplicity – is able to reproduce the observed collective effects. It takes its inspiration[1] from the process of chemotaxis (see [23] for a review) as used by some insects. They create a chemical trace to guide other individuals to food places. This is also the central idea of the active-walker models. In the approach of [21] the pedestrians also create a trace. In contrast to trail formation and chemotaxis, however, this trace is only virtual although one could assume that it corresponds to some abstract representation of the path in the mind of the

[1] Such "learning from nature" is the central idea of a field called *Bionics*.

pedestrians. Its main purpose is to transform effects of long-ranged interactions (e.g. following people walking some distance ahead) into a local interaction (with the "trace"). This allows for a much more efficient simulation on a computer.

2 Basic Principles of the Model

First we discuss some general principles applied in the development of the model [21,22]. To allow an efficient implementation for large-scale computer simulations a discrete model is preferable. Therefore a two-dimensional CA is used with a stochastic dynamics taking into account the interactions between the pedestrians. As mentioned above, similar to chemotaxis, we want to transform long-ranged interactions into local ones. This is achieved by the introduction of so-called *floor fields*. The transition probabilities for all pedestrians depend on the strength of the floor fields in their neighbourhood in such a way that transitions in the direction of larger fields are preferred.

Interactions between pedestrians are repulsive for short distances. One likes to keep a minimal distance to others in order to avoid bumping into them. This is taken into account through hard-core repulsion which prevents multiple occupation of the cells. For longer distances the interaction is often attractive. E.g. when walking in a crowded area it is usually advantageous to follow directly behind the predecessor. Large crowds may also be attractive due to curiosity and in panic situation often herding behaviour can be observed [6].

The long-ranged part of the interaction is implemented through the floor fields. We distinguish two kinds, a *static floor field* and a *dynamic floor field*. The latter models the dynamic interactions between the pedestrians, whereas the static field represents the constant properties of the surroundings.

The dynamic floor field corresponds to a virtual trace which is created by the motion of the pedestrians and in turn influences the motion of other individuals. Furthermore it has its own dynamics, namely through diffusion and decay, which leads to a dilution and finally the vanishing of the trace after some time.

The static floor field does not change with time since it only takes into account the effects of the surroundings. Therefore it exists even without any pedestrians present. It allows to model e.g. preferred areas, walls and other obstacles. A typical example can be found in [8] where the evacuation from a room with a single door is examined. Here the strength of the static field decreases with increasing distance from the door.

The introduction of the floor fields allows for a very efficient implementation on a computer since now all interactions are local. We have translated the *long-ranged spatial interaction* into a *local interaction with "memory"*. The number of interaction terms in other long-ranged models, e.g. the social-force model, grows proportionally to the square of the number of particles whereas in our model it grows only linearly. Another advantage can be seen in the case of complex geometries, e.g. as shown in Fig. 1. Here it is assumed that the typical interaction range is ξ. However, due to the presence of walls not all particles within this range interact with each other. Therefore one needs an algorithm to check whether two particles “see” each other and interact or whether the interaction is blocked by some obstacle.

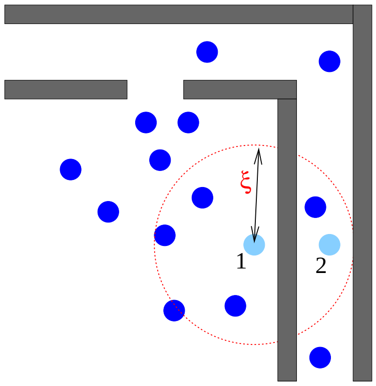
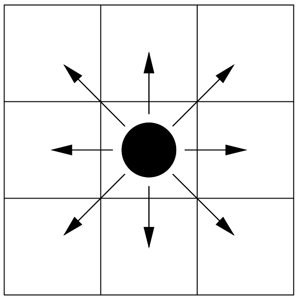


Fig. 1. Typical situation in a complex geometry: Particles 1 and 2 do not interact with each other due the wall between them.

Furthermore we do not need to provide the pedestrians with some sort of “intelligence”. The floor fields are sufficient to achieve the formation of complex structures and collective effects by means of self-organization. Even for the evacuation scenario [8,11,21] described above the knowledge about the floor fields is enough to find the exit. Therefore the pedestrians behave like simple ‘particles’ in a field without explicit intelligence. Since we also not make detailed assumptions about the human behaviour it allows us to keep the model simple. Nevertheless it is able to reproduce many of the basic phenomena.

In contrast to vehicular traffic the time needed for acceleration and braking is negligible in pedestrian motion. The velocity distribution of pedestrians is sharply peaked [24]. These facts naturally lead to a model where the pedestrians have a maximal velocity $v_{\max} = 1$, i.e. only transitions to neighbour cells are allowed. Furthermore, a larger $v_{\max}$, i.e. pedestrians can move more than just one cell per timestep, would be harder to implement in two dimensions and reduce the computational efficiency. The number of possible target cells increases quadratically with the maximal velocity. Furthermore it has to be checked whether the path is blocked by other pedestrians. This might even be ambigious for diagonal motion and crossing trajectories. Also higher velocity models lead to timescales which are much too small (see Sec. 3).

For some applications it is useful to introduce another field called *matrix of preference* which encodes the preferred walking direction and speed of each pedestrian. From this direction, a 3×3 matrix is constructed which contains the probabilities for a move of the particle. The central element describes the probability for the particle not to move at all, the remaining eight correspond to a move to one of the neighbouring cells[2] (see Fig. 2). The probabilities can directly be related to observable quantities, namely the velocity and the longitudinal and transversal standard deviations (see [21,25] for details). In the simplest case the pedestrian is allowed to move in one direction only without fluctuations. In the corresponding matrix of preference only one element is one and all others are zero. In the following it is assumed that a matrix of preference is given at every timestep for each pedestrian. In principle, it can differ from cell to cell depending on the geometry and aim of the pedestrians. Therefore it can be combined with some model for route selection which assigns certain routes to each pedestrian.



$M_{-1,-1}$	$M_{-1,0}$	$M_{-1,1}$
$M_{0,-1}$	$M_{0,0}$	$M_{0,1}$
$M_{1,-1}$	$M_{1,0}$	$M_{1,1}$

Fig. 2. A particle, its possible transitions and the associated matrix of preference $M = (M_{ij})$.

3 Definition of the model

CA are discrete in space, time and state variables. The area available for pedestrians is divided into cells of approximately 40×40 cm^2 which is the typical space occupied by a pedestrian in a dense crowd [26]. Each cell can either be empty or occupied by exactly one particle (pedestrian). For special situations it might be desirable to use a finer discretization, e.g. such that each pedestrian occupies four cells instead of one, but we restrict to the simplest case which is sufficient for the applications studied here.

The update is done in parallel for all particles. This introduces a timescale into the dynamics which can roughly be identified with the reaction time t_{reac}. The existence of a timescale in the dynamics of the model is essential if one wants to make *quantitative predictions* for real processes. In the deterministic limit, corresponding to the maximal possible walking velocity in our model, a single pedestrian (not interacting with others) moves with a velocity of one cell per timestep, i.e. 40 cm per timestep. Empirically the average velocity of a pedestrian is about 1.3 m/s [26]. This gives an estimate for the real time

[2] In most cases motion in diagonal directions is not considered so that the matrix of preference has at most five nonzero elements.

corresponding to one timestep in our model of approximately 0.3 *sec* which is of the order of the reaction time $t_{\rm reac}$ and thus consistent with our microscopic rules. It also agrees nicely with the time needed to reach the normal walking speed which is about 0.5 *sec*. This corresponds to at least $v_{\rm max}$ timesteps if the pedestrian can only accelerate by one unit per timestep. Therefore in models with large $v_{\rm max}$ a timestep would correspond to a real time shorter than the smallest relevant timescale. This makes the model more complicated than necessary and reduces the efficiency of simulations.

We now define the stochastic dynamics of the model by specifying the transition probabilities p_{ij} for a motion to a neighbouring cell in direction[3] (i, j). As explained in Sec. 2 the long-ranged interactions with other pedestrians and the surrounding is incoded in two fields, the dynamic floor field D and the static floor field S, respectively. Furthermore a matrix of preference M can be used to specify the walking direction, speed and fluctuations for each individual. The *transition probability* p_{ij} in direction (i, j) is then determined by all three contributions. Explicitly it is given by

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

D_{ij} and S_{ij} are the strengths of the dynamic and static floor field at the target cell and M_{ij} is the matrix element of the matrix of preference for a motion in the direction (i, j). N is a normalization factor to ensure $\sum_{(i,j)} p_{ij} = 1$ where the sum is over the nine possible target cells. The factor $1 - n_{ij}$, where n_{ij} is the occupation number of the neighbour cell in direction (i, j), takes into account that transitions to occupied cells are forbidden. ξ_{ij} is a geometry factor (obstacle number) which is 0 for forbidden cells (e.g. walls) and 1 else. Finally, we have introduced two coupling constants k_D and k_S so that we can vary the coupling strengths to each field individually.

The actual values of the parameters k_D and k_S depend on the situation. A large k_S implies that the pedestrians choose their path mainly due to the surrounding without being distracted too much by other people. A large coupling k_D to the dynamic field, on the other hand, corresponds to a strong herding behaviour. Here the pedestrian tries to follow the lead of others, e.g. in the case of panics or insufficient knowledge about the surroundings. The effects of these couplings will be discussed in more detail in [8].

As mentioned before, the dynamic floor field is created by the motion of the pedestrians and corresponds to a virtual trace. At $t = 0$ it is zero everywhere. Whenever a particle moves from site (x, y) to one of its neighbours $(x + i, y + j)$, the field D_{xy} at the origin cell is increased by one ($D_{xy} \to D_{xy} + 1$). Thus D_{xy} has only non-negative integer values which can be interpreted as the number of 'bosons' located at site (x, y).

The dynamic floor field is not only changed by the motion of the pedestrians, but it is also subject to diffusion and decay which first leads a spreading and dilution of the trace and finally to its vanishing after some time. Diffusion and decay are controlled by two parameters $\alpha \in [0, 1]$ and $\delta \in [0, 1]$. In each time step

[3] $i, j \in \{-1, 0, 1\}$, see Fig. 2.

of the simulation each boson of the dynamic field D decays with the probability δ and diffuses with the probability α to one of the neighbouring cells.

The update rules of the full model including the interaction with the floor fields then have the following structure:

1. The dynamic floor field D is modified according to its diffusion and decay rules.
2. Using equation (1), for each pedestrian the transition probabilities p_{ij} for a move to an unoccupied neighbour cell (i, j) are determined by the matrix of preference and the local dynamic and static floor fields.
3. Each pedestrian chooses a target cell based on the probabilities of the transition matrix $P = (p_{ij})$.
4. The conflicts arising by any two or more pedestrians attempting to move to the same target cell are resolved (see below).
5. The pedestrians which are allowed to move execute their step.
6. The pedestrians alter the dynamic floor field D_{xy} of the cell (x, y) they occupied before the move.

These rules have to be applied to all pedestrians at the same time (parallel dynamics). This introduces a timescale into the dynamics (see Sec. 2) which corresponds to approximately 0.3 *sec* of real time and allows e.g. to translate evacuation times measured in computer simulations into real times.

One detail is worth mentioning. If a particle has moved in the previous timestep the boson created then is not taken into account in the determination of the transition probability. This prevents that pedestrians get confused by their own trace.

Finally we like to comment on step 4, the resolution of conflicts which occur if $m \geq 2$ particles choose the same destination cell in step 3. This is relevant for high density situations. In order to avoid multiple occupancies of cells only one particle is allowed to move while the others keep their position. There are different ways to choose this particle. E.g. the winning particle can be picked at random with probability $1/m$ or according to the relative probabilities p_{ij} with which each particle chose their target [21]. For the problems studied here and in [8] the details of the conflict resolution turned out to play no important role.

4 Collective phenomena

In this section we show that the model is indeed able to reproduce the collective effects mentioned in Sec. 1. As most prominent example we want to discuss lane formation out of a randomly distributed group of pedestrians. This corresponds to a spontaneous breaking of the symmetry of the particle number distribution in space. Simulations show that an even as well as an odd number of lanes may be formed. The latter corresponds to a spontaneous breaking of the left-right symmetry of the system.

Fig. 3 shows simulations of a rectangular corridor which is populated by two species of pedestrians moving in opposite directions. Parallel to the direction of

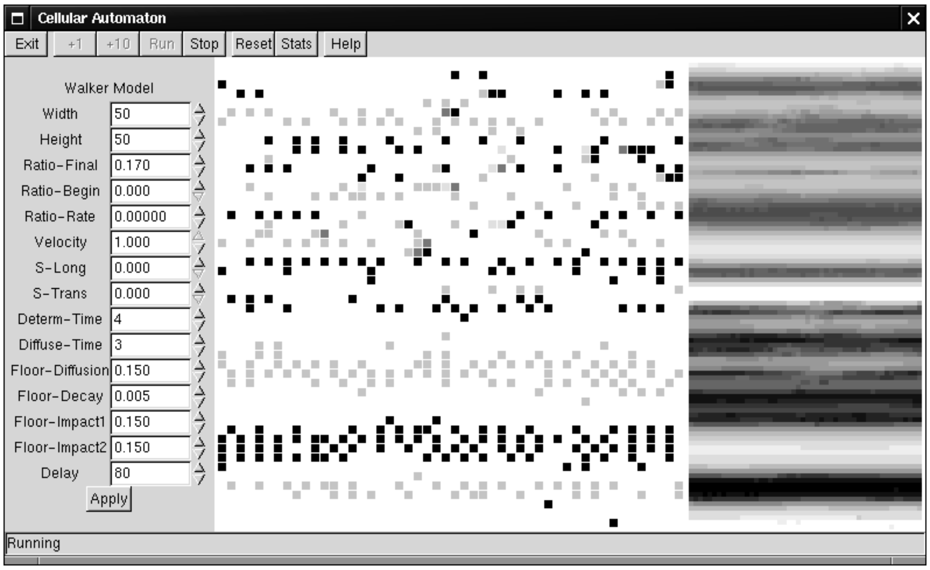


Fig. 3. Snapshot of a simulation of counterflow along a corridor. The left part shows the parameter control. The central window is the corridor and the light and dark squares are right- and left-moving pedestrians, respectively. The right part shows the floor fields for the two species.

motion the existence of walls is assumed. Orthogonal to the direction of motion both periodic and open boundary conditions have been investigated. With periodic boundary conditions, the density of pedestrians is fixed for each run. It is ensured that the overall number of pedestrians is evenly divided by the numbers for the different species, each interacting with its own dynamic floor field[4]. For open boundaries, we fix the rate at which pedestrians enter the system at the boundaries. The pedestrians leave the system as soon as they reach the opposite end of the corridor. Fig. 3 shows the graphical frontend running a simulation of a small periodic system. Lanes have already formed in the lower part of the corridor and can be spotted easily, both in the main window showing the cell contents and the small windows on the right showing the floor field intensity for the two species.

The formation of the lanes can also clearly be seen in the velocity profile (Fig. 4) which has been measured at a cross section perpendicular to the direction of flow. In a certain density regime, the lanes are metastable. Spontaneous fluctuations can disrupt the flow in one lane causing the pedestrians to spread and interfere with other lanes. Eventually the system can run into a jam by this mechanism.

Another typical feature of pedestrian behaviour are oscillations of the direction of flow when two groups of opposite walking direction are facing each other at a tight spot like a narrow door [4]. In our simulations we can observe oscil-

[4] The static floor field is set to $S_{xy} = 0$ in this example.

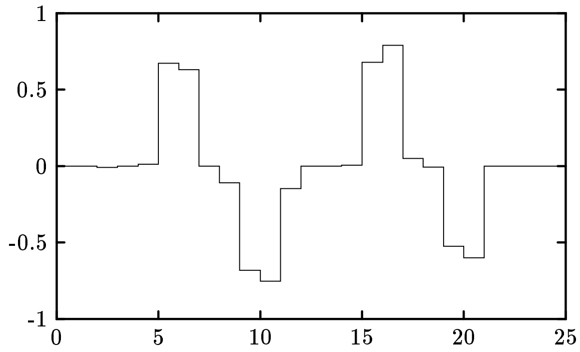


Fig. 4. Velocity profile of a periodic system with $\rho = 0.12$.

lations on two time scales (provided that the parameters are suitably chosen): An exchange between a blocked situation and a flow in both directions is the main result. Inside the blocked period small groups of only one species can break through. This is illustrated in Fig. 5. These breaks can alternate between the two species and can therefore be interpreted as oscillations.

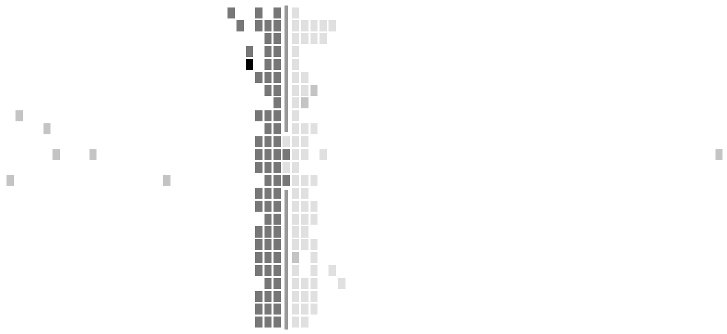


Fig. 5. Oscillations of the direction of flow: A group of particles of the same species break through a blockade at a door (located in the center of the figure, with a width of 4 cells).

Apart from lane formation and oscillations of the direction of flow at doors also other phenomena, e.g. the formation of flow patterns at intersections, have been observed [9,21,25]. Since the model captures the main phenomena correctly and is extremely efficient in computer simulations it might be an ideal tool for evacuation simulations [11].

5 Conclusions

We have introduced a stochastic cellular automaton to simulate pedestrian behaviour, focussing on the general concept. The key mechanism is the introduction of floor fields which act as a substitute for pedestrian intelligence and leads to collective phenomena. These floor fields make it possible to translate spatial long-ranged interactions into non-local interactions in time. The latter can be implemented much more efficiently on a computer. Another advantage is an easier treatment of complex geometries.

The general idea in our model is similar to chemotaxis. However, the pedestrians leave a virtual trace rather than a chemical one. This virtual trace has its own dynamics (diffusion and decay) which e.g. restricts the interaction range (in time). It is realized through a dynamic floor field which allows to give the pedestrians only minimal intelligence and to use local interactions. Together with the static floor field it offers the possibility to take different effects into account in a unified way, e.g. the social forces between the pedestrians or the geometry of the building.

We have shown that the approach is able to reproduce the fascinating collective phenomena observed in pedestrian dynamics. As an example the formation of lanes in counterflow and oscillations of the flow direction at bottlenecks have been discussed in Sec. 4.

In Part II [8] we investigate the influence of the coupling strengths on the dynamics. There it is also demonstrated that the approach can be used for simple evacuation simulations. Therefore the model is a good starting point for realistic applications [11]. Further information can also be found on the webpage [27].

The description of pedestrians using a cellular automaton approach allows for very high simulation speeds. Pedestrian crowds of a few hundred people can be simulated 10 to 100 times faster than real time. Therefore, we have the possibility to extract the complete statistical properties of our model using Monte Carlo simulations.

Finally it should be emphasized that we have presented only the basic ideas of the approach. For realistic applications modifications might be appropriate, e.g. smaller cell sizes or inertia effects [21].

Acknowledgement: I like to thank my collaborators Carsten Burstedde, Ansgar Kirchner and Kai Klauck for their input and many inspiring discussions.

References

1. D. Chowdhury, L. Santen and A. Schadschneider: Phys. Rep. **329**, 199 (2000)
2. D. Helbing: `cond-mat/0012229`
3. D. Helbing, I. Farkas, P. Molnar and T. Vicsek: in M. Schreckenberg and S.D. Sharma (Ed.), "Pedestrian and Evacuation Dynamics" (Springer 2001)
4. D. Helbing and P. Molnar: Phys. Rev. **E51**, 4282 (1995)
5. D. Helbing, I. Farkas and T. Vicsek: Phys. Rev. Lett. **84**, 1240 (2000)
6. D. Helbing, I. Farkas and T. Vicsek: Nature **407**, 487 (2000)
7. D. Helbing: these proceedings
8. A. Kirchner and A. Schadschneider: *Cellular automaton simulations of pedestrian dynamics and evacuation processes*, these proceedings

9. C. Burstedde, A. Kirchner, K. Klauck, A. Schadschneider and J. Zittartz: in M. Schreckenberg and S.D. Sharma (Ed.), “Pedestrian and Evacuation Dynamics” (Springer 2001)
10. N. Ohi, M. Ikai and K. Nishinari: these proceedings
11. A. Kirchner and A. Schadschneider: in preparation
12. D. Helbing, F. Schweitzer, J. Keltsch and P. Molnar: Phys. Rev. **E56**, 2527 (1997)
13. D. Helbing, J. Keltsch and P. Molnar: Nature **388**, 47 (1997)
14. M. Fukui and Y. Ishibashi: J. Phys. Soc. Jpn. **68**, 2861, 3738 (1999)
15. M. Muramatsu, T. Irie and T. Nagatani: Physica **A267**, 487 (1999)
16. M. Muramatsu and T. Nagatani: Physica **A275**, 281 (2000); **A286**, 377 (2000)
17. H. Klüpfel, T. Meyer-König, J. Wahle and M. Schreckenberg: in *Theory and Practical Issues on Cellular Automata*, S. Bandini, T. Worsch (Eds.), Springer (2000); see also these proceedings
18. O. Biham, A.A. Middleton and D. Levine: Phys. Rev. **A46**, R6124 (1992)
19. P.G. Gipps and B. Marksjös: Math. and Comp. in Simulation **27**, 95 (1985)
20. K. Bolay: Diploma Thesis, Stuttgart University (1998)
21. C. Burstedde, K. Klauck, A. Schadschneider and J. Zittartz: Physica **A295**, 507 (2001)
22. A. Schadschneider: in M. Schreckenberg and S.D. Sharma (Ed.), “Pedestrian and Evacuation Dynamics” (Springer 2001)
23. E. Ben-Jacob: Contemp. Phys. **38**, 205 (1997)
24. L.F. Henderson: Nature **229**, 381 (1971)
25. C. Burstedde: Diploma Thesis, Universität zu Köln (2001); available for download at `http://www.burstedde.de/carsten/diplom.html`
26. U. Weidmann: *Transporttechnik der Fussgänger*, Schriftenreihe des IVT **80**, ETH Zürich (1992)
27. `http://www.thp.uni-koeln.de/~as/as.html`