CA Approach to Collective Phenomena in Pedestrian Dynamics

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Abstract. Pedestrian dynamics exhibits a variety of fascinating and surprising collective phenomena (lane formation, flow oscillations at doors etc.). A 2-dimensional cellular automaton model is presented which is able to reproduce these effects. 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. Due to its simplicity the model allows for faster than real time simulations of large crowds.

1 Introduction

The investigation of traffic flow using methods from physics has attracted a lot of interest during the last decade [1,2]. Due to their simplicity, especially cellular automata models (CA) have been at the focus of attention. In contrast to highway traffic, pedestrian flow [3] is truely 2-dimensional and effects due to counterflow become important. This gives rise to several self-organization phenomena not observed in vehicular traffic.

The most successful model for pedestrian dynamics so far is the so-called social force model [4]. Here pedestrians are treated as particles subject to long-ranged forces induced by the social behaviour of the individuals. This idea leads to equations of motion similar to Newtonian mechanics.

Most cellular automata models for pedestrian dynamics proposed so far [5, 6,7] and can be considered as generalizations of the BML model for city traffic [8]. However, these models are not able to reproduce all the collective effects observed empirically. The same is true for more sophisticated models [9,10].

In [11,12,13,14] 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 from the process of chemotaxis as used by some insects. They create a chemical trace to guide other individuals to food places. This is also the central idea of active-walker models [15,16] used for the description of human and animal trails. In the approach of [11] the pedestrians also create a trace which, in contrast to trail formation and chemotaxis, is only virtual although one could assume that it corresponds to some abstract representation of the path in the mind of the pedestrians. Its main purpose is to transform effects of long-ranged interactions

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(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.

Many interesting collective effects and self-organization phenomena have been observed in pedestrian dynamics (for a review, see [2,3,17]):

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 where the flow is limited by a door or narrowing and is important for practical applications, especially evacuation simulations. Other types of jamming occur in the case of counterflow where two groups of pedestrians mutually block each other.

Lane formation: In counterflow, i.e. two groups of people moving in opposite directions, a kind of spontaneous symmetry breaking occurs (see Sec. 3.1). 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.

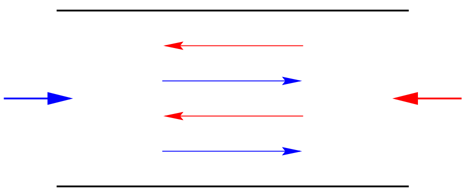


Fig. 1. Illustration of lane formation in counterflow in a narrow corridor.

Oscillations: In counterflow at bottlenecks, e.g. doors, one can observe oscillatory changes of the direction of motion (see Fig. 2). Once a pedestrian is able to pass the bottleneck it becomes easier for others to follow in the same direction until somebody is able to pass the bottleneck in the opposite direction.

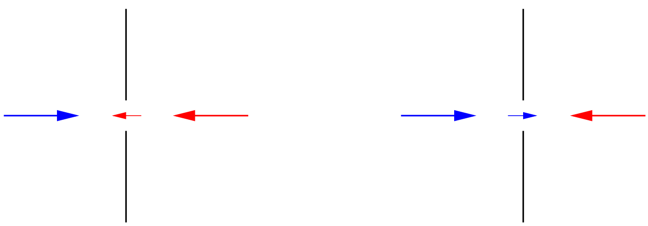


Fig. 2. Illustration of flow oscillations at a door with counterflow.

Panics: In panic situations, many counter-intuitive phenomena can occur. In the faster-is-slower effect [18] a higher desired velocity leads to a slower movement of a large crowd. In the freezing-by-heating effect [19] increasing the fluctuations can lead to a more ordered state. For a thorough discussion we refer to [17,18] and references therein.

2 Definition of the Model

First we discuss some general principles applied in the development of the model [11,12]. To allow an efficient implementation for large-scale computer simulations a discrete model is preferable. Therefore a two-dimensional CA is used with stochastic dynamics taking into account the interactions between the pedestrians. Similar to chemotaxis, we transform long-ranged interactions into local ones. This is achieved by introducting so-called *floor fields*. The transition probabilities for all pedestrians depend on the strength of the floor fields in their neighbourhood such that transitions in the direction of larger fields are preferred.

Interactions between pedestrians are repulsive for short distances ('private sphere'). This is incorporated through hard-core repulsion which prevents multiple occupation of the cells. For longer distances the interaction is often attractive, e.g. in crowded areas it is usually advantageous to walk directly behind the predecessor. Large crowds may be attractive due to curiosity and in panic situation often herding behaviour can be observed [18].

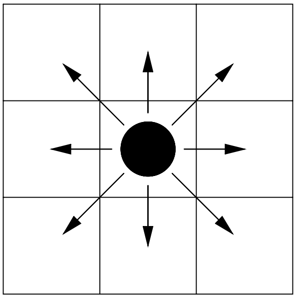
The long-ranged part of the interaction is implemented through the floor fields. We distinguish two kinds, a *static floor field* and a *dynamic floor field*. The latter models the dynamic interactions between the pedestrians, whereas the static field represents the constant properties of the surroundings.

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 (diffusion and decay) which leads to a dilution and vanishing of the trace after some time. We assume the dynamic field to be discrete. Therefore the integer field strength D_{xy} can be interpreted as number of bosonic particles located at (x, y).

The static floor field does not change with time since it only takes into account the effects of the surroundings. It allows to model e.g. preferred areas, walls and other obstacles. A typical example can be found in Sec. 3.2 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"*. Therefore the number of interaction terms grows only linearly with the number of particles. Another advantage of local interactions can be seen in the case of complex geometries. Due to the presence of walls not all particles within the interaction range interact with each other. Therefore one needs an algorithm to check whether two particles "see" each other or whether the interaction is blocked by some obstacle. All this is not necessary here.

For some applications it is useful to introduce a *matrix of preference* which encodes the preferred walking direction and speed of each pedestrian. It is a 3×3 matrix (see Fig. 3) where the matrix elements M_{ij} can directly be *related to observable quantities*, namely the average velocity and its fluctuations [11].



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

Fig. 3. A particle, its possible transitions and the associated matrix of preference $M = (M_{ij})$.

The area available for pedestrians is divided into cells of approximately $40 \times 40\ cm^2$ which is the typical space occupied by a pedestrian in a dense crowd [20]. Each cell can either be empty or occupied by exactly one particle (pedestrian). Apart from this simplest variant it is also possible to use a finer discretization, e.g. pedestrians occupying four cells instead of one.

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 [21]. 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 $v_{\max}$ would be harder to implement in two dimensions and reduce the computational efficiency.

The stochastic dynamics of the model is defined by specifying the transition probabilities p_{ij} for a motion to a neighbouring cell (von Neumann or Moore neighbourhood) in direction (i,j). The *transition probability* p_{ij} in direction (i,j) is determined by the contributions of the static and dynamic floor fields S_{ij} and D_{ij} and the matrix of preference M_{ij} at the target cell:

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

N is a normalization factor to ensure $\sum_{(i,j)} p_{ij} = 1$ where the sum is over the 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. The coupling constants k_D and

k_S allow to vary the coupling strengths to each field individually. Their actual values depend on the situation and will be discussed in Sec. 3.2.

The update rules of the full model including the interaction with the floor fields then have the following structure [11,12]:

1. The dynamic floor field D is modified according to its diffusion and decay rules: Each boson of the dynamic field D decays with probability δ and diffuses with probability α to one of the neighbouring cells.
2. From (1), for each pedestrian the transition probabilities p_{ij} are determined.
3. Each pedestrian chooses a target cell based on the probabilities p_{ij}.
4. The conflicts arising by $m > 1$ pedestrians attempting to move to the same target cell are resolved. To avoid multiple occupancies of cells only one particle is allowed to move while the others keep their position. In the simplest case the moving particle is chosen randomly with probability $1/m$ [11].
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. The field D_{xy} at the origin cell is increased by one ($D_{xy} \to D_{xy} + 1$).

These rules are applied to all pedestrians at the same time (parallel dynamics). This introduces a timescale which corresponds to approximately 0.3 *sec* of real time [11] by identifying the maximal walking speed of 1 cell per timestep with the empirically observed value 1.3 m/s for the average velocity of a pedestrian [20]. The existence of a timescale allows 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. One can even go a step further and introduce 'inertia' [11] which enhances the transition probability in the previous direction of motion. This can be incorporated easily by an additional factor d_{ij} in eq. (1) such that $d_{ij} > 1$ if the pedestrian has moved in the *same* direction in the previous timestep and $d_{ij} = 1$ else.

3 Results

3.1 Collective Phenomena

As most prominent example of self-organization phenomena we discuss lane formation out of a randomly distributed group of pedestrians. Fig. 4 shows a simulation of a corridor which is populated by two species of pedestrians moving in opposite directions. Parallel to the direction of motion the existence of walls is assumed. Both species interact with their own dynamic floor field only. Lanes have already formed in the lower part of the corridor and can be spotted easily, both in the main window showing the positions of the pedestrians and the small windows on the right showing the floor field intensity for the two species. Simulations show that an even as well as an odd number of lanes may be formed,

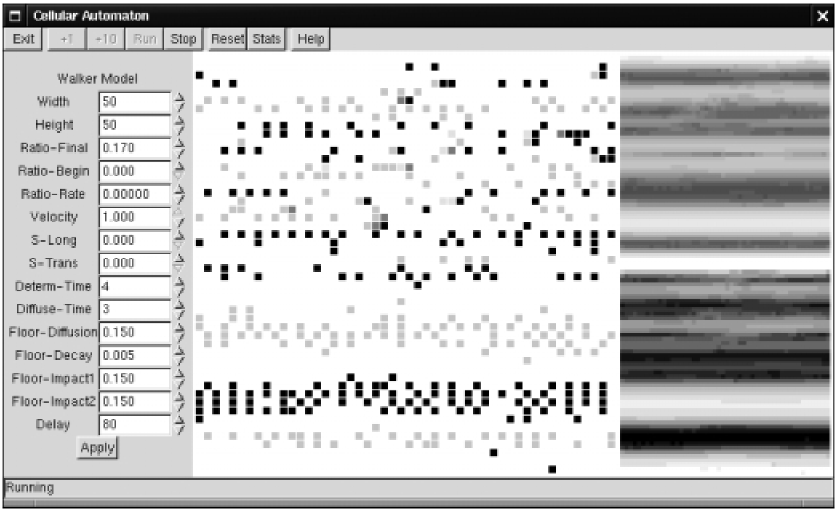


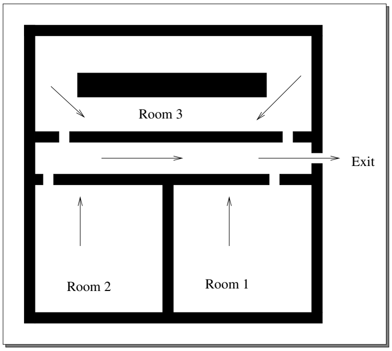
Fig. 4. Snapshot of a simulation of counterflow along a corridor illustrating lane formation. The central window is the corridor and the light and dark squares are right- and left-moving pedestrians, respectively. In the lower part of the corridor lanes have already formed whereas the upper part still disordered. The right part shows the floor fields for right- and left movers in the upper half and lower half, respectively. The field strength is indicated by the greyscale.

the latter corresponding to a spontaneous breaking of the left-right symmetry. 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.

Apart from lane formation we have also observed oscillations of the direction of flow at doors and the formation of roundabout-like flow patterns at intersections [11,13]. Therefore the model captures – despite its simplicity – the main phenomena correctly which is important for practical applications, e.g. evacuation simulations or the optimization of escape routes.

3.2 Influence of the Floor Fields

In order to elucidate the influence of the coupling parameters k_S and k_D we investigated an evacuation process in a simple geometry, namely a large room of $L \times L$ cells with one door [14]. In the simulations, N particles are distributed randomly in the beginning, corresponding to a density $\rho = N/L^2$. All information about the location of the exits is obtained from the floor fields. The field values of the static floor field S increase in the direction of the door and are determined by some distance metric [14]. Fig. 5 shows a complex structure and the corresponding static floor field. The field strength is proportional to the distance to the nearest exit measured using a Manhattan metric.



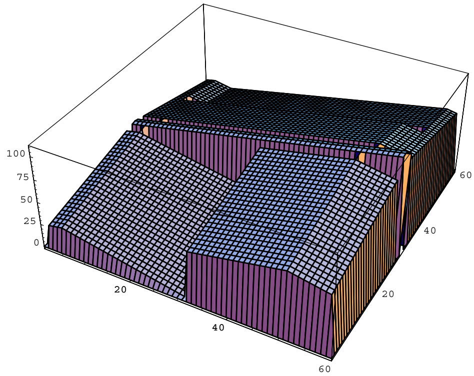
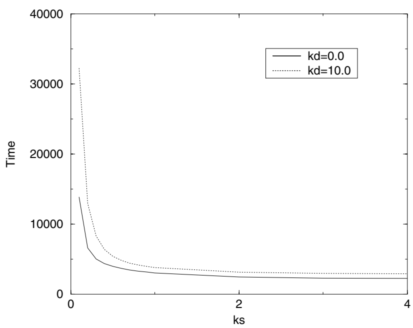


Fig. 5. Static floor field (right) for a rather complex geometry (left).

k_S, the coupling to the static field, can be viewed as a measure of the knowledge about the location of the exit. A large k_S implies an almost deterministic motion to the exit on the shortest possible path. For vanishing k_S, the individuals will perform a random walk and just find the exit by chance. So the case $k_S \ll 1$ is relevant for processes in dark or smoke-filled rooms where people do not have full knowledge about the location of the exit. For fixed sensitivity parameter k_D, the evacuation time decrease monotonically with increasing k_S (see Fig. 6(a)). k_S can be interpreted as some kind of inverse temperature for the degree of information about the inanimate surrounding.



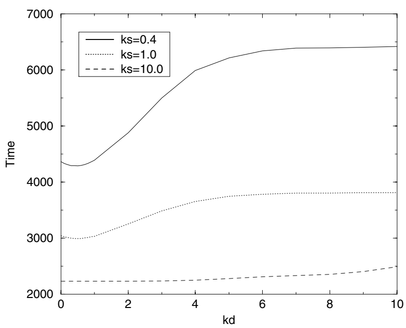


Fig. 6. Averaged evacuation times for a large room with an initial particle density of $\rho = 0.3$ and $\delta = 0.3$, $\alpha = 0.3$ for **(a)** fixed k_D, and **(b)** fixed k_S.

The parameter k_D controls the tendency to follow the lead of others. A large value of k_D implies a strong herding behaviour as observed in panics [18]. For fixed k_S (see Fig. 6(b)), the evacuation times converge to maximal values for growing k_D. The most interesting point is the occurence of minimal evacuation times for non-vanishing small values of the sensitivity parameter k_D of the dynamic field. Therefore a small interaction with the dynamic field, which is proportional to the velocity-density of the particles, is of advantage. It represents some sort of minimal intelligence of the pedestrians. They are able to detect regions of higher local flow and minimize their waiting times.

3.3 Friction Effects

In [22] a friction parameter μ has been introduced to describe clogging effects between the pedestrians. Whenever $m > 1$ pedestrians attempt to move to the same target cell, the movement of all involved particles is denied with the probability μ, i.e. all pedestrians remain at their site. This means that with probability $1 - \mu$ one of the individuals moves to the desired cell. Which particle actually moves is then determined by the rules for the resolution of conflicts described in Sec. 2. If μ is high, the pedestrians handicap each other trying to reach their desired target sites. As we will see, this local effect can have enormous influence on macroscopic quantities like flow and evacuation time [22]. Note that the kind of friction introduced here only influences interacting particles, not the average velocity of a freely moving pedestrian.

Fig. 7(a) shows the influence of the friction parameter on the evacuation time T for the scenario described in Sec. 3.2. As expected, T is monotonically increasing with μ. The strongest effect can be observed in the ordered regime,

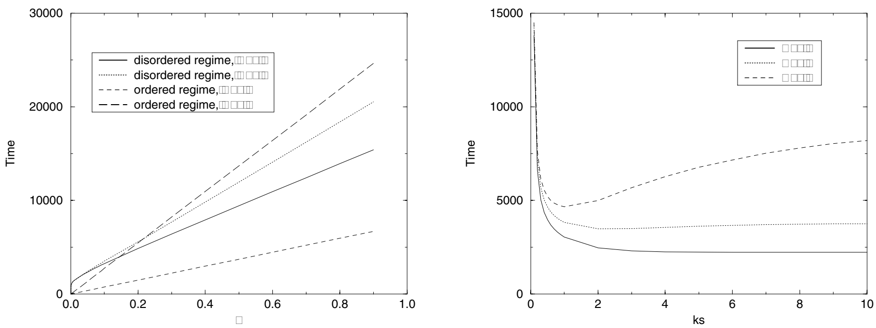


Fig. 7. Dependence of evacuation times on the friction parameter μ (a) in the ordered (k_S large, k_D small) and disordered regimes (k_S small, k_D large) and (b) as a function of k_S for $\rho = 0.3$.

i.e. for strong coupling k_S and weak coupling k_D. Here the evacuation time is mainly determined by the clogging at the door. For large values of μ it increases strongly due to the formation of self-supporting arches. This "arching" effect is well-known from studies of granular materials [23].

For fixed μ and varying coupling strength k_S a surprising result can be observed (Fig. 7(b)). For $\mu = 0$ the evacuation time is monotonically decreasing with increasing k_S since for large coupling to the static field the pedestrians will use the shortest way to the exit. For large μ, $T(k_S)$ shows a minimum at an intermediate coupling strength $k_S \approx 1$. This is similar to the faster-is-slower effect described in Sec. 1: Although a larger k_S leads to a larger effective velocity in the direction of the exit, it does not necessarily imply smaller evacuation times.

4 Conclusions

We have introduced a stochastic cellular automaton to simulate pedestrian behaviour[1]. 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.

The floor fields 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. We have shown that the approach is able to reproduce the fascinating collective phenomena observed in pedestrian dynamics. Furthermore we have found surprising results in a simple evacuation scenario, e.g. the nonmonotonic dependence of the evacuation time on the coupling to the dynamic floor field. Also friction effects (Sec. 3.3), related to the resolution of conflict situations where several individuals want to occupy the same space, can lead to counterintuitive phenomena.

References

1. Chowdhury, D., Santen, L., Schadschneider, A.: Statistical physics of vehicular traffic and some related systems. Phys. Rep. **329** (2000) 199–329
2. Helbing, D.: Traffic and related self-driven many-particle systems. Rev. Mod. Phys. **73** (2001) 1067–1141
3. Schreckenberg, M., Sharma, S.D. (Ed.): *Pedestrian and Evacuation Dynamics*, Springer 2001
4. Helbing, D., Molnar, P.: Social force model for pedestrian dynamics. Phys. Rev. **E51** (1995) 4282–4286
5. Fukui, M., Ishibashi, Y.: Self-organized phase transitions in cellular automaton models for pedestrians. J. Phys. Soc. Jpn. **68** (1999) 2861–2863
6. Muramatsu, M., Irie, T., Nagatani, T.: Jamming transition in pedestrian counter flow. Physica **A267** (1999) 487–498

[1] Further information and Java applets for the scenarios studied here can be found on the webpage `http://www.thp.uni-koeln.de/~as/as.html`.

7. Klüpfel, H., Meyer-König, T., Wahle, J., Schreckenberg, M.: Microscopic simulation of evacuation processes on passenger ships. in *Theory and Practical Issues on Cellular Automata*, S. Bandini, T. Worsch (Eds.), Springer (2000)
8. Biham, O., Middleton, A.A., Levine, D.: Self-organization and a dynamical transition in traffic-flow models. Phys. Rev. **A46** (1992) R6124–R6127
9. Gipps, P.G., Marksjös, B.: A micro-simulation model for pedestrian flows. Math. and Comp. in Simulation **27** (1985) 95–105
10. Bolay, K.: Nichtlineare Phänomene in einem fluid-dynamischen Verkehrsmodell. Diploma Thesis, Stuttgart University (1998)
11. Burstedde, C., Klauck, K., Schadschneider, A., Zittartz, J.: Simulation of pedestrian dynamics using a 2-dimensional cellular automaton. Physica **A295** (2001) 507–525
12. Schadschneider, A.: Cellular automaton approach to pedestrian dynamics - Theory. in [3], p. 75–85
13. Burstedde, C., Kirchner, A., Klauck, K., Schadschneider, A., Zittartz, J.: Cellular automaton approach to pedestrian dynamics - Applications. in [3], p. 87–97
14. Kirchner, A., Schadschneider, A.: Simulation of evacuation processes using a bionics-inspired cellular automaton model for pedestrian dynamics. Physica **A** (in press)
15. Helbing, D., Schweitzer, F., Keltsch, J., Molnar, P.: Active walker model for the formation of human and animal trail systems. Phys. Rev. **E56** (1997) 2527–2539
16. Chowdhury, D., Guttal, V., Schadschneider, A.: Cellular-automata model of ant-trail and vehicular traffic: similarities and differences. cond-mat/0201207
17. Helbing, D., Farkas, I., Molnar, P., Vicsek, T.: Simulation of pedestrian crowds in normal and evacuation situations. in [3], p. 21–58
18. Helbing, D., Farkas, I., Vicsek, T.: Simulating dynamical features of escape panic. Nature **407** (2000) 487–490
19. Helbing, D., Farkas, I., Vicsek, T.: Freezing by heating in a driven mesoscopic system. Phys. Rev. Lett. **84** (2000) 1240–1243
20. Weidmann, U.: Transporttechnik der Fussgänger. Schriftenreihe des IVT **80**, ETH Zürich (1992)
21. Henderson, L.F.: The statistics of crowd fluids. Nature **229**, 381 (1971)
22. Kirchner, A., Nishinari, K., Schadschneider, A.: Friction effects and clogging in a cellular automaton model for pedestrian dynamics. in preparation.
23. Wolf, D.E., Grassberger, P. (Ed.): *Friction, Arching, Contact Dynamics*, World Scientific 1997