Cellular automaton simulations of pedestrian dynamics and evacuation processes

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Abstract. We present applications and numerical results for a bionics-inspired cellular automaton approach to pedestrian dynamics [1,2]. The model is able to reproduce collective effects and self-organization phenomena encountered in pedestrian traffic, e.g. lane formation in counterflow. Here we present an analysis of the quantitative impact of the so-called sensitivity parameters k_S and k_D during evacuation processes. Furthermore the model is applied to the problem of optimization of evacuation times.

1 Introduction

In [1] a new two-dimensional cellular automaton model for the description of pedestrian dynamics has been introduced. Further details, especially concerning the definition of the model, can be found elsewhere in these proceedings [2]. The basic idea is similar to the phenomenon of chemotaxis. The transition probabilities for the motion of the pedestrians are determined using so-called *floor fields* in such a way that a movement in direction of higher fields is more likely. The *static floor field S* does not evolve with time and is not changed by the presence of the pedestrians. Such a field can be used to specify regions of space which are more attractive. The *dynamic floor field D* is a virtual trace left by the pedestrians and has its own dynamics, i.e. diffusion (described by a diffusion constant $\alpha \in [0,1]$) and decay (with decay constant $\delta \in [0,1]$). It is used to model an attractive interaction between the particles.

Here we want to show the model's usefulness for deepening our understanding of the complex problems of evacuation processes. Realistic procedures of evacuations are in general not uniform, highly ordered behaviour of the pedestrians as well as panic situations are observed. As we will see in the following, the model is able to reproduce many of these collective social phenomena.

We will focus on evacuation processes from a large room with one or more doors. Fig. 1(a) shows S for a lattice of size 33×33 with one exit of width five cells. For each lattice site S is calculated using a special distance metric so that the field values are increased in the direction to the door. Fig. 1(b) shows a 3-d plot of the dynamic field D in the final stages of an evacuation process.

2 Evacuation Simulations

In the following we describe results of simulations of a typical situation, i.e. the evacuation of a large room (e.g. in case of fire). At this we focus on the influence

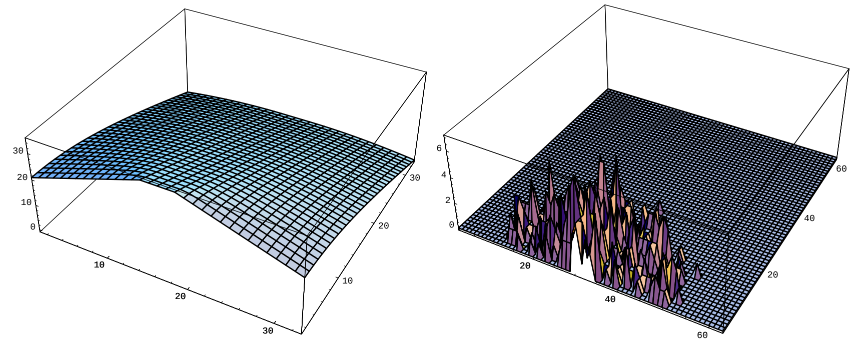

Fig. 1. Evacuation from a large room with a single door: **(a)** static floor field S; **(b)** dynamic floor field D in the final stages of the evacuation.

of the sensitivity parameters k_D and k_S on the evacuation times. As we will see the variation of these parameters leads to many interesting collective phenomena between the pedestrians. Concluding we give an example of the relevance of our model for practical applications at safety estimations in architectural planning.

2.1 The impact of sensitivity parameters

The value of k_S, the coupling to the static field, can be viewed as a measure of the knowledge of the pedestrians about the location of the exit. A large k_S implies a motion to the exit on the shortest possible path. For vanishing k_S, on the other hand, the people 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.

The parameter k_D for the coupling to the dyamic field controls the tendency to follow the lead of others. A large value of k_D implies a strong herding behaviour which has been observed in the case of panics [3].

We consider a grid of size 63×63 sites with an exit of one cell in the middle of one wall. The particles are initially distributed randomly and try to leave the room. The only information they get is through the floor fields. Fig. 2 shows typical stages of the dynamics for an initial particle density of $\rho = 0.3$, which means 1116 particles. In the middle picture of Fig. 2 a half-circle jamming configuration in front of the door is easy to spot. A typical feature of the dynamics is a radial motion of 'holes' created by particles escaping through the door.

The evacuation times are averaged over 500 samples and strongly depend on the sensitivity parameters k_D and k_S. Fig. 3(a) shows the evacuation times for fixed sensitivity parameter k_D of the dynamic field and variable sensitivity parameter k_S of the static field. The averaged evacuation times are always measured in update time steps. With the generic timescale of the model [1,2] it is easy to translate that into a real time value. Let us first consider the case of $k_D = 0$, i.e. no coupling to the dynamic field. In Fig. 3(a) one can see the influence of k_S. For $k_S \to 0$ the pedestrians do not sense the strength of the field.

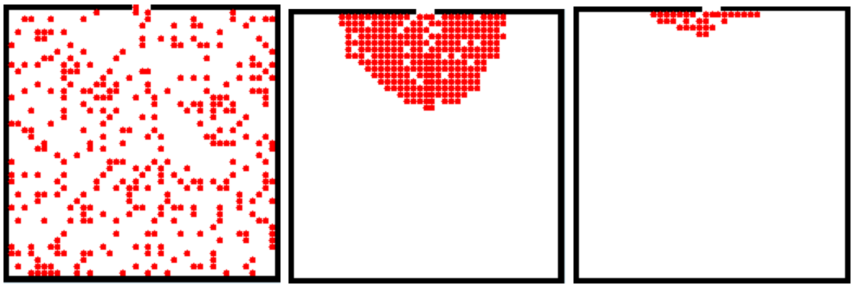

Fig. 2. Typical stages of the dynamics: **(a)** beginning evacuation ($t = 0$); **(b)** middle stages; **(c)** end stage of evacuation with only a few particles left

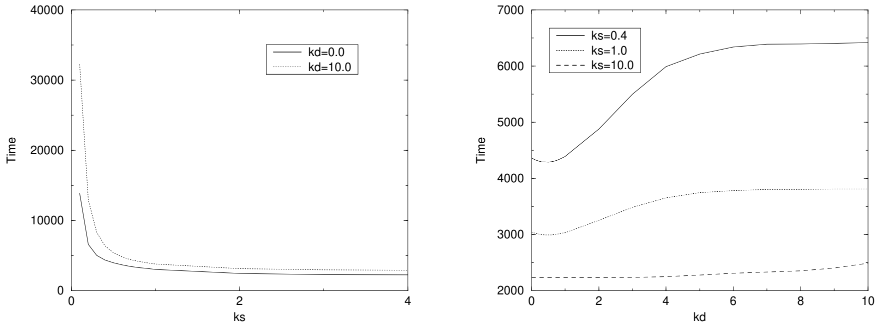

Fig. 3. Averaged evacuation times for a large room (Fig. 2) with an initial particle density of $\rho = 0.3$ and $\delta = 0.3$, $\alpha = 0.3$ for **(a)** fixed k_D, and **(b)** fixed k_S.

Therefore they do not have any guidance through the surroundings and perform a pure random walk which leads to a maximal value of the evacuation time for $k_S = 0$. For $k_S \to \infty$ they have full information about the shortest distance to the door and the evacuation time converges towards a minimal value. The movement of the particles becomes almost deterministic. Therefore k_S can be interpreted as some kind of inverse temperature for the degree of information about the inanimate surrounding of the pedestrians.

In the same way the sensitivity parameter k_D of the dynamic field works as an inverse temperature for the information about the virtual trace. If k_S is turned on from zero to infinity, a non-zero value of k_D only means additional noise to the pedestrians, the evacuation times are increased for higher coupling strength to k_D (see Fig. 3(a)).

Much more interesting is the behavior for fixed k_S. In this case the evacuation times for various sensitivity parameters k_D are shown in Fig. 3(b). They converge to maximal values for growing sensitivity parameter k_D of the dynamic field. 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. This effect also depends on the value of the diffusion parameter α and becomes most pronounced in the limit $\alpha \to 0$. 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.

If the coupling to the dynamic field is further increased, the evacuation times increase again from the small regime of the minimal times to maximal values. The interaction with other pedestrians becomes more and more unfavourable, one can compare this to the arising of a panic situation. The weaker the coupling to the static field S is, the higher are the evacuation times: the particles than have less information of the unanimate surrounding (for example they cannot find the way to the door because of smoke in a fire situation).

The influence of the diffusion parameter α of the dynamic field in the regime of minimal evacuation times strongly depends on the particle density ρ. In

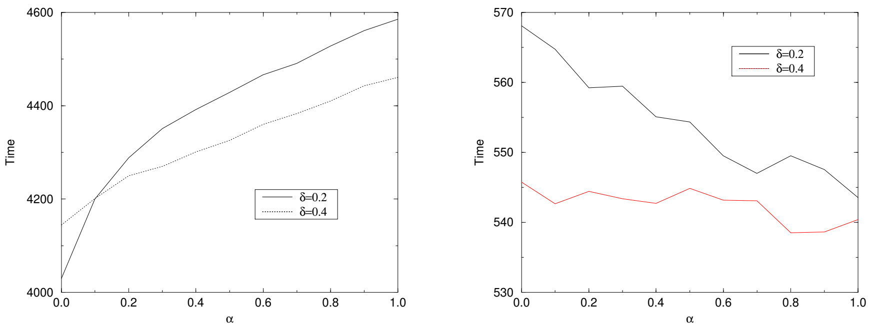

Fig. 4. Averaged evacuation times for a large room (Fig. 2) for two densities, variable α and $k_S = k_D = 0.4$: **(a)** $\rho = 0.3$; **(b)** $\rho = 0.004$.

Fig. 4(a) one can see that in the high density regime an increasing diffusion parameter α increases the evacuation times for arbitrary decay parameter δ. In that case diffusion of the field only means noise for the particles. In the low density regime one finds the opposite behaviour: an increasing value of α leads to a minimization of the evacuation time. In the low density regime the diffusion of the dynamic field therefore leads to a higher degree of information for the particles and to favorably long-ranged interactions between them.

Thus three main regimes for the behaviour of the particles can be distinguished. For strong coupling to k_S and very small coupling to k_D we find an *ordered regime* where particles only react to the static floor field and the behaviour than is in some sense deterministic. The *disordered regime* characterized by strong coupling to k_D and weak coupling to k_S leads to a maximal value of the evacuation time. The behaviour here is typical for panic situations. Between these two regimes an *optimal regime* exists where the combination of interaction with the static and the dynamic floor fields minimizes the evacuation time.

Fig. 5(a) shows the influence of an increasing particle density for the evacuation times in the three main regimes. In all regimes the curves increase almost

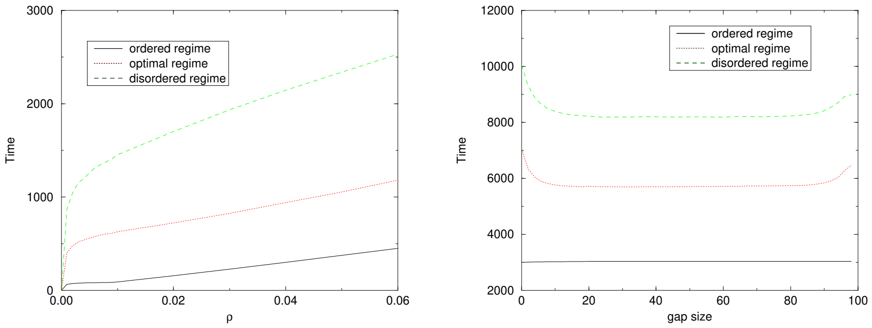

Fig. 5. Average evacuation times for a large room **(a)** with one door as a function of the density and **(b)** with two doors as function of the gap between the doors.

linearly. Only for very small densities one finds a very strong increase of the evacuation times with increasing density. For a much more detailed investigation of all this, see [4].

2.2 Room with two doors

As a simple example for safety estimations in architectural planing we investigate how evacuation times change if a gap between two doors is increased from zero to a maximal value. For that we consider again an ordinary room with no internal structure of grid size 102×102. We start with one door of width two cells in the middle of one wall. Then the door is split into two doors of one cell each which are separated by gaps ranging from 2 to 98 (Fig. 6(b) and(c)). Fig. 6 shows typical stages of the dynamics for different gap sizes. Averaged evacuation times are measured for all three main regimes introduced in Sec. 2.1. Depending on the regime, Fig. 5(b) shows a strong influence of the size of the gap for small and for large gaps. In the ordered regime, the evacuation time is almost uninfluenced by the gap size. The reason is the almost deterministic movement of the particles which do not interact with each other through the dynamic floor field D. In the other two regimes, however, the value of the gap can have a large influence due to the strong interaction effects through D. For both the optimal and the disordered regime one finds minimized evacuation times for a wide area of the gap length ranging from about 20 to 80 cells. For small gaps the evacuation times increase due to the interactions between the pedestrians. For large gaps

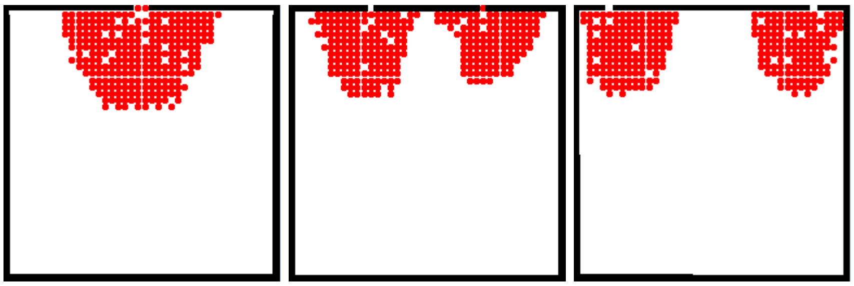

Fig. 6. **(a)** No gap between doors, **(b)** medium gap size between doors, **(c)** doors at the boundaries.

the presence of the side walls has a negative effect (Fig. 6(c)) and so again the evacuation times increase. For intermediate gaps the crowd of pedestrians will be subdivided into smaller parts (Fig. 6(b)), leading to more favorable interactions between them.

3 Conclusions

We have studied simple evacuation processes using a recently introduced stochastic cellular automaton for pedestrian dynamics which makes use of an idea similar to chemotaxis. Due to its simplicity the model allows very high simulation speeds and is very well suited for the optimization of evacuation procedures in complex situations.

We have focussed on the influence of the coupling strengths k_S and k_D on the evacuation time. Interesting nontrivial collective phenomena could be observed, e.g. the nonmonotonic dependence of the evacuation time on the coupling to the dynamic floor field. A more detailed account of our results can be found in [4].

References

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