Many-particle simulation of the evacuation process from a room without visibility

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We study the evacuation process from a smoky room by means of experiments and simulations. People in a dark or smoky room are mimicked by “blind” students wearing eye masks. The evacuation of the disoriented students from the room is observed by video cameras, and the escape time of each student is measured. We find that the disoriented students exhibit a distinctly different behavior compared with a situation in which people can see and orient themselves. Our experimental results are reproduced by an extended lattice gas model taking into account the empirically observed behavior. Our particular focus is on the mean value and distribution of escape times. For a large number of people in the room, the escape time distribution is wide because of jamming. Surprisingly, adding more exits does not improve the situation in the expected way, since most people use the exit that is discovered first, which may be viewed as “herding effect” based on acoustic interactions. Moreover, the average escape time becomes minimal for a certain finite number of people in the dark or smoky room. These non-linear effects have practical implications for emergency evacuation and the planning of safer buildings.

I. INTRODUCTION

During the last decade, many observed self-organization phenomena in traffic flows [1–5] and pedestrian streams [6–9] have been successfully reproduced with physical methods. This has not only stimulated research in granular, biological, and colloid physics [10–12]. It has also encouraged physicists to study evacuation processes [13–15], since it has been shown that many aspects of crowd stampedes can be understood by driven many-particle models [16,17]. The empirical observations have many common features with driven granular media.

Evacuation processes have been studied by the use of various simulation models. The typical models of pedestrian motion are based on molecular dynamics methods [6,16,17], lattice gas models [7,18–24], or cellular automata [9,14,15,25]. In simulations of evacuation processes, it has been mostly assumed that visibility is good. However, this is often not the case during fire emergencies, as smoke or a failure of the electrical power supply reduce the orientation significantly. Because of the toxic effects of smoke, fast evacuation is particularly important, but little is known about the behavior of people under conditions of bad or no visibility.

In this study, we will therefore focus on the investigation of the evacuation process from a smoky room without visibility. In favour of video recordings, we mimic this situation by requiring our test persons to wear eye masks. This allows us to study not only qualitative features, but also quantitative outcomes, which is relevant for reliable predictions of evacuation times and the planning of safer buildings or pedestrian facilities. From our video recordings, we have evaluated the characteristic behavior and the escape times in well-controlled experiments (see Sec. II). In Section 3, these experiments are reproduced with an extended lattice gas model of pedestrian flows with model parameters calibrated to the data. Despite of the simplicity of the model, it can successfully reproduce the characteristic escape behavior under conditions of no visibility and the empirical escape times in a semi-quantitative way. Moreover, we identify two interesting effects: First, the average escape time becomes minimal for a specific finite number of people, who are initially in the room. Second, adding more exits does not increase the efficiency of evacuation in the expected way.

II. EXPERIMENT

We have experimentally studied the evacuation of blind students from an empty classroom, which is schematically illustrated in Figure 1. Each student wore an eye mask. The exact width of the classroom was $W = 4.2$ m and its length $L = 5.5$ m. There were no obstacles in the classroom, i.e. desks and chairs were moved aside (to form the boundary). Moreover, the room had one exit of width 0.5 m. Two video cameras 1 and 2 were located within and in front of the classroom. A cameraman was able to observe all the students by video camera 1. The other cameraman could observe the students who escaped through the exit by video camera 2. We investigated two cases:
Correspondingly, at time $t = 0$, there were either (a) one student or (b) 10 students in the classroom, and each student was standing at a random place within a central area of the room. Before the experiment, all students were forced by the cameraman to turn around themselves. In the result, they lost their directional orientation. All students moved to seek for the exit as soon as a cameraman shouted a word of command. The evacuation process was then recorded by the two video cameras.

We have first studied the case (a) of single disoriented students with eye masks. By careful analysis of the video recordings, we have determined the trajectory and escape time of each student. The individual escape time was defined as the time elapsed between the shouting of the command and the moment when the respective student left the room through the exit. Figure 2 shows four typical trajectories of a single student until he successfully escaped from the room. His face direction at the initial position is indicated by an arrow. At first, the student turned slightly, and then he moved slowly towards one of the walls of the room. As soon as he touched the boundary, he followed it, after he had chosen the right-hand or left-hand direction at random, because of the loss of directional memory. As soon as he found the exit, he left the room. Note that the following of the wall differs significantly from the behavior assumed in the evacuation simulations of Ref. [16], where individuals “hitting” a wall where “reflected”. It is, therefore, interesting and important to check, whether the conclusions for the evacuation of a group of people are to be revised. It will turn out that our new simulations are an independent, experimentally supported confirmation of the previous findings, which were obtained for a hypothetical pedestrian behavior under conditions of smoke.

In Figure 2, the escape time obtained from the experiment is shown below each trajectory. One can see that the disoriented students sometimes take the shorter way and at other times the longer way. Thus, the escape time depends highly on the randomly chosen direction. We repeated the experiment 10 times with 10 different students. The mean escape time of $t_e = 31.5$ sec was obtained by averaging over all experiments, but the variance was large, as expected.

Next, we have studied the case (b) of 10 disoriented students with eye masks. Initially, the 10 students were standing at random places close to the center of the room. By careful analysis of our video recordings, we have determined the trajectories and escape times of all 10 students. Figure 3 shows a photo of the evacuation of students from the room at time $t = 16$ sec. The students move along the wall. Figure 4 shows the time evolution of the evacuation process for 10 students. The patterns (a)-(d) were obtained at times $t = 0$ sec, 5 sec, 10 sec, and 15 sec. Numbered circles represent the 10 disoriented students, whose face directions are indicated by arrows. The students turned slightly at first, and moved slowly towards one of the walls of the room. As soon as they touched a wall of the room, they followed it in one of the two possible directions. However, as soon as one or two students managed to leave the room, the remaining students noticed the location of the exit accoustically. Then, the remaining students managed to find the exit much faster. When a student met another one, they went together along the wall into the same direction. They left the room as soon as they reached the exit.

We determined the escape times of all students by careful analysis of our video recordings of 10 repetitions of the experiment. The average escape time of the ten students was 22.1 sec. However, the escape time of the fastest student was 9.8 sec, while the value of the slowest student was 34.3 sec. Thus, the distribution of escape times was again rather wide. Notice that the average escape time of 22.1 sec for 10 students is significantly lower than the 31.5 sec for a single student! This lower value of escape time is due to the reason that, when one or two students managed to leave the room successfully, the remaining students noticed the location of the exit and inverted their direction, if appropriate.

For comparison, we performed an escape experiment for 10 students without eye masks corresponding to a room with normal visibility. Figure 5 shows the time evolution of the evacuation process for all 10 students. The patterns (a)-(d) were obtained at times $t = 0$ sec, 1 sec, 3 sec, and 5 sec. Their face directions are indicated by arrows. The students turned instantly towards the exit and then moved into its direction very fast. When the arrival rate of students exceeded the capacity of the exit, students were queueing, i.e. a crowd of students was forming in front of the exit due to jamming. The average escape time of the 10 students was 6.54 sec. This value is significantly lower than the 22.1 sec for 10 disoriented students with eye masks.

Therefore, the evacuation process from a room with no visibility is qualitatively and quantitatively different from the evacuation under normal conditions. For this reason, it is necessary and important to develop a simulation model of the evacuation of people, which allows to assess the efficiency of escape and the safety of buildings under different conditions, in particular under conditions of no visibility.
III. MANY-PARTICLE SIMULATION

In the following, we will describe a simple model which allows to reproduce our experimental findings for the evacuation of a smoky room in a semi-quantitative way. Here, we will simulate the pedestrian flow by the use of a lattice gas model, but it would be also possible to use the social force model of pedestrian behavior [6,16,17]. We have implemented the following characteristics of disoriented people:

(1) Each person turns slightly at first and moves towards one of the walls.
(2) He chooses the right-hand or left-hand direction at random as soon as he reaches a wall.
(3) Afterwards, he moves along the wall.
(4) When one or two students have managed to leave the room (after the “exploration phase”), the remaining students turn into the direction of the exit as well.

Each disoriented student is represented by a walker on a square-diagonal lattice with \(L \times W\) sites reflecting the classroom. We choose the lattice spacing as 0.4 m, since the typical space occupied by a pedestrian in a dense crowd is about 0.4 m x 0.4 m. We therefore use \(L = 14\) and \(W = 11\). The classroom is connected to the outer space through a single exit represented by one site. Figure 1 shows a schematic illustration. An empty circle represents a student in the classroom. In reasonable agreement with the empirical observations, we assume that each walker performs a biased-random walk on the square-diagonal lattice until he reaches the boundaries of the room [26]. Initially, each walker chooses randomly one of the eight directions on the square-diagonal lattice. The walker is then biased with respect to this direction, which represents the desired walking direction of the student. The biased random walker is allowed to move not only to the nearest-neighbor sites, but also to the next-nearest neighbor sites (in the diagonal directions).

Figure 6 illustrates two of all possible configurations of a biased random walker on the square-diagonal lattice, where bias is assumed in the upward direction. Configuration (a) shows the situation of being able to move to all the nearest-neighbor and next-nearest-neighbor sites, when these are not occupied by other walkers. The arrows indicate the possible directions in which the walker can move. The transition probabilities of the walker into the 8 directions are given by

\[
p_{t,y} = D/3 + (1 - D)/8 = p_{t,y}^{(a)}
\]

\[
p_{t,x,y} = p_{t,-x,y} = D/6 + (1 - D)/8 = p_{t,x,y}^{(a)}
\]

\[
p_{t,x} = p_{t,-x} = D/9 + (1 - D)/8 = p_{t,x}^{(a)}
\]

\[
p_{t,-y} = p_{t,x,-y} = p_{t,-x,-y} = D/27 + (1 - D)/8 = p_{t,-y}^{(a)},
\]

where \(D\) is the parameter representing the bias, \(p_{t,y}\) is the transition probability in \(y\)-direction, and the superscript \(\text{a}\) refers to configuration (a). Specifically, \(p_{t,y}^{(a)}\) indicates the transition probability into the \(y\)-direction in configuration (a), \(p_{t,x,y}^{(a)}\) the transition probability into the \(x\)- and \(y\)-direction, i.e. into diagonal direction, etc. In the following simulation, we set \(D=0.99\). The transition probability is then \(p_{t,y}^{(a)} = 0.33\). This value agrees with the average speed 0.33 m/s obtained from the experiment. Therefore, we identify one time step in our simulations with one second.

Figure 6(b) shows the configuration in which another walker occupies one of the nearest-neighbor sites. The location of the other walker is indicated by a cross. Then, the transition probabilities into the remaining 7 directions are given by

\[
p_{t,x,y} = p_{t,-x,y} = p_{t,x,y}^{(a)} + \frac{p_{t,x,y}^{(a)}}{2p_{t,x,y}^{(a)} + 2p_{t,x}^{(a)} + 3p_{t,-y}^{(a)}} \times p_{t,y}^{(a)}/7
\]

\[
p_{t,x} = p_{t,-x} = p_{t,x}^{(a)} + \frac{p_{t,x}^{(a)}}{2p_{t,x,y}^{(a)} + 2p_{t,x}^{(a)} + 3p_{t,-y}^{(a)}} \times p_{t,y}^{(a)}/7
\]
\[ p_{t,-y} = p_{t,x,-y} = p_{t,-x,-y} = p_{t,-y}^{(a)} + \frac{p_{t,-y}^{(a)}}{2p_{t,x,y}^{(a)} + 2p_{t,x}^{(a)} + 3p_{t,-y}^{(a)}} \times p_{t,y}^{(a)}. \] (2)

For the other possible configurations, the transition probabilities of walkers are specified analogously. Therefore, the explicit expressions are omitted to save manuscript space.

In our simulations, we assume that initially (at time \( t = 0 \)), all disoriented students stand at some location in the classroom without any directional memory. In the next time step \((t = 1)\), each student starts moving in order to escape from the room. Until he reaches the boundaries (a wall), he performs a biased random walk according to the model sketched above. For each random walker, we assume a constant bias into the desired direction defined by the first step. All walkers are updated once every time step in a random sequential way as, in reality, the students move asynchronously (in contrast to the synchronized movement of soldiers in a military corps). When a walker reaches the wall, he chooses the direction to the left or to the right randomly with probability 1/2. After this choice, he moves along the wall. Furthermore, when one walker manages to leave the room, the remaining walkers adopt their desired direction to the direction of the exit. When a walker reaches the exit, he is removed from the simulation. Excluded volume effects are taken into account by preventing multiple occupation of the same site, i.e. each site contains only one individual walker or it is empty.

Our numerical results are displayed in Figs. 7 to 13. Figure 7 shows representative trajectories when there is only one walker. The related escape times for trajectories (a) to (d) were \( t_e = 31 \) sec, \( t_e = 32 \) sec, \( t_e = 41 \) sec, and \( t_e = 23 \) sec. These values are indicated below the trajectories. For illustrative reasons, from the many simulated trajectories, we have selected the examples (a)-(d) which looked similar to the ones displayed in Fig. 2, which were obtained experimentally. The mean value of 30.1 sec for the simulated escape time was obtained by averaging over 100000 samples, as compared to an average escape time of 31.5 sec in our experiments. Figure 8 shows the probability density of escape times for one student, obtained from 100000 simulation runs. The probability density exhibits a rather wide distribution, but the mean escape time agrees well with the one obtained from the experiment.

Figure 9 shows the time evolution of the evacuation process of 10 persons according to our simulations. The representative patterns (a)-(d) were obtained at times \( t = 0 \) sec, 5 sec, 10 sec, and 15 sec. Full circles represent 10 walkers, whose face directions are indicated by arrows. The behavior of the 10 simulated walkers was qualitatively the same as the one observed in our experiments (see Fig. 4). The mean value of the escape time was reduced as in our experiments, but with 27.1 sec, the simulation value was a pessimistic estimate of the experimental value.

Similarly, Figure 10 shows the simulated time evolution of the evacuation process for 20 persons. The patterns (a)-(d) were obtained at times \( t = 0 \) sec, 5 sec, 10 sec, and 20 sec. The behaviors of the 20 simulated walkers was similar to those of 10 persons. However, jamming appeared near the exit at \( t = 20 \) sec, because the arrival rate of walkers exceeds the capacity of the exit.

We have determined the probability density distribution of escape times of a finite number of walkers from 100000 simulation runs. Figures 11(a)–(d) show, respectively, the plots of the probability density of escape times for 5, 10, 15, and 20 persons. Each circle represents 10 walkers, whose face directions are indicated by arrows. The probability density distribution has approximately a Gaussian shape. With an increasing number of walkers, the probability density distribution of escape times for the nth person becomes narrower, i.e. the variance decreases. Figure 12 shows the probability density distributions of the overall escape times for all persons in the cases of 1, 5, 10, 15, and 20 walkers. Up to 10 walkers, the probability density distribution becomes slightly narrower with an increasing number of walkers, but the distribution becomes rather wide when the number of walkers exceeds 10. For less than 10 walkers, the efficiency of the escape is enhanced by the presence of other persons who may discover the exit, but the escape is obstructed by the other persons for more than 10 walkers, which is due to jamming near the exit.

Figure 13 shows the plot of the first walker’s mean escape time as a function of the overall number of walkers initially present in the room. With an increasing number of walkers, the escape time of the first escaped walker decreases. This is, because the chances to discover the exit increase with the presence of more people.

**IV. SIMULATIONS WITH TWO DOORS**

We will now study the effect of two exits on the evacuation process from a room with no visibility (e.g. a room with heavy smoke) by means of simulations. The second exit is assumed to be located on the opposite side of the room.

The simulations basically agree with the ones for one exit, but we will consider two different cases: In scenario A, as soon as one of the walkers has found an exit, the other walkers are assumed to recognize the location of this exit acoustically and to move into its direction, as in the scenario with one exit. However, in scenario B we assume
that walkers do not recognize or ignore the discovery of an exit by other walkers. In scenario A, the second door is practically unused, as the walkers turn towards the exit discovered first. Consequently, an additional door does not double the flow of escaped persons and does not reduce the average escape time by a factor of two, as planners would usually assume. It mainly reduces the exploration time until a door is discovered. In contrast, in scenario B walkers use the two alternative exits approximately with the frequency that planners usually assume. Figure 14 shows the average evacuation time for a room with one and two doors, respectively. Circles, squares, and triangles indicate, respectively, the simulation results for the situation with one exit, for scenario A and scenario B. Figure 15 displays the overall evacuation time as a function of the initial number of walkers. When the initial number of persons is increased, the difference in the escape times between scenarios A and B becomes large. This result urgently calls for an acoustic guidance of people towards the exit in evacuation situations, in order to use the evacuation capacities of all available exits, and avoid unnecessary jamming. In situations with normal visibility, there is a tendency to have a load balancing between alternative exits [27].

V. SUMMARY

Focussing on the individual escape times, we have presented experimental results on the evacuation of disoriented students from a classroom with no visibility. The behavior of the disoriented students was very characteristic. They moved slowly towards one of the walls of the room and then along the wall. As soon as one of the persons managed to leave the room, the other ones recognized the location of the exit acoustically and moved into this direction. This reduced the average escape time in the case of one door, but it produced unnecessary jamming in the case of multiple doors. Therefore, acoustic guidance towards the doors would significantly increase the efficiency of usage of alternative doors, decrease the average escape times, and increase the chances of survival in emergency situations.

Despite of the stochastic nature of pedestrian flows, the empirical observations could be semi-quantitatively reproduced by an extended lattice gas model, i.e. a stochastic many-particle approach. In particular, we could successfully reproduce the empirically observed behavior of persons in a room without visibility: For example, the average escape time per person becomes minimal for a certain number of persons (see Fig. 14), as the chances to find the exit increase with the number of persons (see Fig. 13), but obstructions due to jamming at the exit dominate for a higher number of persons (see Fig. 12). As a consequence, the model could be used to identify not only the expected escape times as a function of the number of people in a dark or smoky room, but it could also help to identify the probability distribution of escape times. This is of practical importance for the assessment of the safety of buildings in emergency situations.
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FIGURE CAPTIONS

FIG. 1. Schematic illustration of the classroom of width $W = 4.2$ m and length $L = 5.5$ m, in which desks, chairs, and other obstacles have been moved aside. There is only one exit in the front of the classroom, the width of which is 0.5 m. Two video cameras 1 and 2 were located within and in front of the classroom. In our simulations, a square-diagonal lattice of $W = 11$ sites and $L = 14$ sites is used.

FIG. 2. Four typical trajectories of a student until he successfully escapes from the room. His face direction at the initial position is indicated by an arrow. Below each trajectory, the escape time obtained from the experiment is indicated.

FIG. 3. Photo of the evacuation of students from the room at $t = 16$ sec.

FIG. 4. Time evolution of the evacuation process of 10 students without visibility of the exit. The patterns (a)-(d) were obtained at $t = 0$ sec, 5 sec, 10 sec, and 15 sec. Numbered circles represent 10 disoriented students with eye masks, whose face directions are indicated by arrows.

FIG. 5. Time evolution of the evacuation process for 10 students in a room with normal visibility. The patterns (a)-(d) were obtained at $t = 0$ sec, 1 sec, 3 sec, and 5 sec. Their face directions are indicated by arrows.

FIG. 6. Two of all possible configurations of a biased-random walker on the square-diagonal lattice, where bias is applied to the upward direction. Configuration (a) shows the situation of being able to move to all the nearest-neighbor and next-nearest-neighbor sites. The arrows indicate the possible directions in which the walker can move. Configuration (b) shows the situation in which another walker occupies one of the nearest-neighbor sites, which is indicated by a cross.

FIG. 7. Representative trajectories obtained from the simulation when there is only one walker. The escape times obtained are shown below the trajectories.

FIG. 8. Plot of the probability density of the simulated escape time for a single walker.

FIG. 9. Simulated time evolution of the evacuation process of 10 persons. The patterns (a)-(d) were obtained at $t = 0$ sec, 5 sec, 10 sec, and 15 sec. Full circles represent 10 students, whose face directions are indicated by arrows.

FIG. 10. Simulated time evolution of the evacuation of 20 persons. The patterns (a)-(d) were obtained at $t = 0$ sec, 5 sec, 10 sec, and 20 sec.

FIG. 11. Plots of the probability density of the simulated escape times for (a) 5, (b) 10, (c) 15, and (d) 20 persons. In each figure, the probability density distributions are shown for the 1st, 5th, 10th, 15th, 20th, and all persons.

FIG. 12. Probability density distributions of the simulated escape times for all persons in the case of 1, 5, 10, 15, and 20 walkers.

FIG. 13. Plot of the mean escape time of the first escaped walker as a function of the overall number of walkers who are initially present in the room.

FIG. 14. Plot of the average escape time as a function of the initial number of walkers. Circles represent the results for one single exit. In the 2-exit simulation, the average escape time is only reduced a little, as walkers orient towards the exit which has been discovered first, which produces jamming at one door (scenario A, see the squares). The expected significant reduction in the average escape time is only found, if walkers do not react to the discovery of a door by other walkers (scenario B, see the triangles).

FIG. 15. Plot of the overall evacuation time of all walkers as a function of the initial number of persons. A second exit reduces the overall evacuation time with respect to the situation with one exit (circles), but it does not reduce it by a factor of 2. If people orient towards the first discovered door (scenario A), the overall escape time is mainly reduced by the earlier discovery of an exit (squares). However, the overall escape time is normally much higher than in the hypothetical scenario B, for which we assume that the discovery of an exit by other people is not recognized or ignored, and both exits are equally used (triangles).
FIG. 1.

t_e=39sec

t_e=25sec

t_e=23sec

t_e=38sec
FIG. 8. Probability density $p(te)$ for escape time $te$. The line indicates the behavior for a single person.
FIG. 10.

(a)
(b)
Probability density $p(te)$

Escape time $te$

(c)
FIG. 11.
FIG. 12.
FIG. 13.
FIG. 14.
FIG. 15.