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On modelling the influence of group formations in a crowd

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Inspired by doubts from social scientists on the validity of computer models that see a crowd as a pure aggregation of individuals, we develop a mathematical model for group formation within crowds. It is based on a few simple characteristics. Most importantly, small groups stick together as they thread their way through a crowd. Additionally, groups have a tendency to walk abreast to ease communication. Through simulation, we establish that the occurrence of groups significantly impacts crowd movement, namely evacuation times. Further, we complement and validate the simulations by a small experiment: a classroom egress. The simulation results match the measurements qualitatively. We get a good quantitative match after calibrating the supposed desire to communicate while walking—and hence to walk abreast. We conclude that it is one of the crucial parameters to calibrate the group model against reality. While working on a mathematically complete model, a new gap between the mathematical modelling and the social sciences emerged: some model assumptions are based on the modeller's intuition rather than on sociological or psychological insight validated by the scientific community. We hope the findings—and resulting suggestions—will in return inspire new cooperation between the disciplines.

Introduction

'Families survive together or die together'—a fact that few in the community of crowd researchers and modellers seem to doubt. The authors of the present paper, all of them mathematicians or computer scientists, have been inspired by this critical comment from social scientist Annette Spellerberg (personal communication, 2009) on our previous work: the modelling of large crowds as an aggregation of individuals.

A crowd at a large event is often dominated by small groups (Aveni, 1977). Larger groups may again separate into smaller subgroups (James, 1951). In our specific case,

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we are interested in a crowd leaving a football stadium (Bogusch *et al.*, 2009). Groups stay together during an evacuation. In fact, there is empirical evidence that making contact with affiliated persons takes precedence over individual flight (Sime, 1983; Aguirre *et al.*, 1998). Even without prior close relationship, a shared identity may arise in an emergency situation and may make individuals stay closely together during the evacuation (Drury *et al.*, 2009). In view of this, how reliable are aggregate simulators when predicting crowd behaviour or planning, e.g. evacuations (Drury & Cocking, 2007; Novelli *et al.*, 2010; Spellerberg *et al.*, 2010)? And, how do we find a viable compromise between what social scientists and psychologist know about group behaviour and the restrictions that modellers have to comply with to create an efficient computer simulation?

Encouraged by these questions, we present an attempt to bridge this gap. We suggest a model for formations of small groups or subgroups in crowds that is based on very few and simple assumptions. Most importantly: small groups stick together as they thread their way through a crowd. They tend to walk in formations that facilitate communication (Moussaïd *et al.*, 2010). That is, they can chat with each other without having to turn their heads.

This simple model allows us to observe the effect of groups in a crowd on phenomena like congestion. We establish that the occurrence of groups significantly impacts crowd movement, at least in our model. The intuitive assumption, that the larger the average group size the slower the crowd moves as a whole, is confirmed by simulation. The effect becomes even more prominent at bottlenecks. A real-life experiment again confirms this hypothesis. However, it also shows that the effect may be reversed when the groups are coordinated with the intention to facilitate navigation.

While the outcome of our experiments makes intuitive sense, it also emphasises the need to incorporate groups in crowd simulators. And this creates a new dilemma. How do crowd modellers know what makes a group or even a crowd? And on which situational parameters might this depend? At many points, while creating our own mathematical model, we had to rely on intuition, a fact that we consider with a certain amount of unease. We feel that there is a very great need for cooperation between mathematical modellers, social scientists and psychologists. Thus, throughout the paper we indicate areas where we would like to trigger an in-depth interdisciplinary discussion.

The model

The cellular automaton model for pedestrian movement in relation to other microscopic mathematical models

Our mathematical model is a cellular automaton, where virtual persons move on a plane divided into cells and according to a set of rules that capture the principles of movement. Like many successful pedestrian movement models, among them Helbing & Molnar's (1995) social force model, the cellular automaton is inspired by a number of physical principles. These models assume that movement is governed by forces that act between pedestrians, pedestrians and obstacles, and pedestrians and targets. Most cellular automaton models stretch the analogy to electrodynamics, comparing persons to negatively charged particles that are repulsed by each other and attracted by targets.

In the case of social force models the forces are called 'social forces' emphasising that they should not be based on physics but on human interaction. They are, however, very much like the equations of Newtonian mechanics. As far as inspiration is concerned, the two model approaches are very similar in a modelling sense, both using forces to drive motion.

Social force models and other discrete element methods (DEM) rely on differential equations to express the interdependencies between the virtual persons, targets and obstacles (Langston *et al.*, 2006). Space is not discretised at all, which is often seen as the main advantage compared with computationally faster cellular automata. In a very recent work Moussaïd *et al.* (2011) restrict the social force approach to very crowded situations. Otherwise they use heuristic rules to, as they state themselves, clear the way for a more realistic modelling of collective social behaviour. At this point social groups are not included in the heuristic model.

Cellular automata are, compared with differential equations, a relatively novel mathematical modelling technique. Nagel & Schreckenberg (1992) introduced the concept to modelling highway traffic. Subsequently the idea was very successfully carried over to pedestrian traffic (Klüpfel, 2003). The obvious advantages are very fast simulation speed and intuitive rules that make the model easy to understand for researchers even without rigorous mathematical training. Also, while the rule-based update of the states in time may be inspired by physical analogies, it does not, unlike DEM models to a certain extent, employ Newton's laws of motion or any other physical law. In particular, it is convenient to introduce multi-agent modelling aspects through more refined rules to capture better individual or complex behaviour that cannot be matched by aggregated physical laws. For example, the authors have used multi-agent-type rules in a cellular automaton simulator to model temporary separation and reunion of groups that face an obstacle (Seitz *et al.*, 2011). In fact, one may see cellular automata-based pedestrian models as special cases of multi-agent systems (Dijkstra *et al.*, 2001). The main disadvantages of cellular automata are the artefacts introduced by the coarse discretisation of space into cells. Above all, the underlying cell grid only allows straight movement in directions where the grid points are arranged on a straight line. However, many of these disadvantages can be mitigated to an extent that we feel is acceptable in view of the accuracy that can reasonably be expected from any contemporary pedestrian stream model (Hartmann, 2010; Köster *et al.*, 2010). An alternative to physics-inspired models would be to build a true multi-agent model, where goals and sub-goals of agents are translated into actions triggered by sensory input. Multi-agent models can in principle capture very complex behaviour. However, complex decision rules introduce a multitude of decisional parameters that must be adjusted. This makes validation difficult. In addition, a complex agent structure increases computational effort, as soon as multiple agents are present, which may hamper practical application. Hence, our own solution strategy at this point is to introduce carefully selected agent aspects in the cellular automaton.

Methods of model validation

Parallel to the modelling attempts themselves, a lot of effort has gone into finding a way to measure crowd phenomena so that crowd models can be validated. The leading idea is to use the measured relationship between the density in a crowd and the velocity of the crowd or, equivalently, the flow, for validation. The denser the crowd, the more people get in each other's way: they slow down until all flow stops. In a dense crowd this is, to a certain extent, a physical effect. In a looser crowd we imagine socio-cultural aspects such as the need for personal space to have a great influence. Diagrams depicting this density–flow relationship are often called fundamental diagrams. Early examples are given by Predtechenskii & Milinskii (1969) and Weidmann (1992). More recent work provides experimental evidence that fundamental diagrams capture, at least to some degree, socio-cultural behaviour such as the need for personal space. For example, the speed of Indian participants is apparently less dependent on density than the speed of German participants who seem to have a more passive walking strategy allowing for more space between individuals (Chattaraj *et al.*, 2009). By conducting a series of computer simulations inducing different crowd densities one can investigate whether a model reproduces the density–flow relationship at least roughly. In more advanced models it is possible to calibrate the parameters automatically, so that a given fundamental diagram is faithfully reproduced. This holds, in principle, for both social force models (Höcker & Milbradt, 2009) and cellular automata (Davidich & Köster, 2010). Our own model is capable of calibrating automatically and robustly to measured fundamental diagrams. For research purposes, as in this paper, we calibrate to the widely accepted benchmark fundamental diagram provided by Weidmann (1992) and use the distribution of free-flow velocities associated with it.

The cellular automaton model

We divide the area of observation in a lattice of hexagonal cells. Each cell at each time step has a status: empty or occupied by either a person, an obstacle or a target. Persons enter and leave through sources and targets, namely entrances and exits. The cells are updated by rules that together form the automaton. In principle, triangular, rectangular and hexagonal cells are possible (Schadschneider *et al.*, 2008; Kinkeldey & Rose, 2003). Although square cells seem to be the most popular choice, we prefer a hexagonal grid for its two additional natural directions of movement compared with the square grid (Figure 1). The persons move in a single plane or several planes such as floors. Hence we may restrict ourselves to two spatial dimensions. Usually, the cell size is chosen to accommodate an average sized European male. The simulation dynamics themselves follow a specific kind of sequential update scheme: the cells containing persons are updated in the order the persons have entered the scenario from a source.

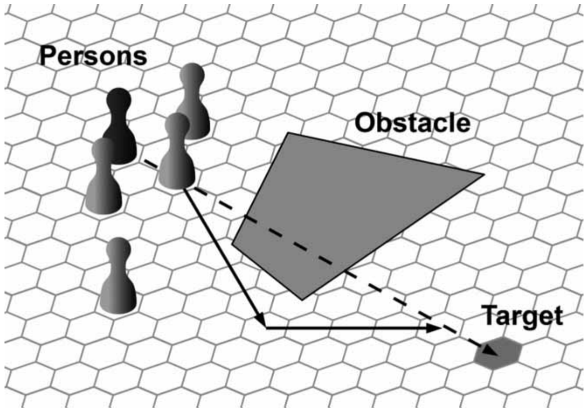


Figure 1. Pedestrians moving on a grid.

The core of the model is contained in the automaton, that is, the set of rules according to which the cell states are updated when the simulation steps forward in time. We borrow the fundamental idea from electrodynamics. In principle, pedestrians are treated as negatively charged particles, say electrons. Therefore pedestrians are attracted by positive charges, such as exits, and repelled by negative charges, such as other pedestrians or obstacles. We would like to emphasise that these repulsive forces can be interpreted as a human's need for personal space. In our model each individual adjusts his or her speed to the speed of the crowd ahead. A field of vision makes the model more realistic. The strength of the need for personal space expressed by the repulsive force and the tendency to reduce speed when nearing a crowd can be calibrated. Mathematically, the forces between pedestrians, targets and obstacles are expressed through a potential field, using the properties of conservative force fields from physics. That is, the forces are expressed as the gradient of a suitable scalar function: the potential. The pedestrians try to minimise the potential during the course of their movement by preferring the empty neighbour cell to which there is the steepest decline of the potential. In this, the model is very similar to many cellular automaton models based on potentials (Burstedde *et al.*, 2001; Hamacher & Tjandra, 2001; Klüpfel, 2003; Rogsch, 2005; Schadschneider *et al.*, 2008; TraffGo, 2010). Finding a smooth and realistic path towards an attracting goal is another challenge. We assume that as long as the path is free, the shortest path is preferred and that obstacles are efficiently skirted. We achieve this by computing the potential with a fast-marching algorithm that mimics the propagation of a wave front from the goal to the pedestrian's position (Hartmann, 2010). The pure electron-based approach clearly has its limitations when modelling human behaviour. The field of vision and the pathfinding strategy are examples of how our model enriches the basic ideas by a number of submodels to compensate for the most relevant shortcomings (Köster *et al.*, 2010). Using the terminology in Schadschneider *et al.* (2008), our model is microscopic, discrete and deterministic with stochastic aspects, rule based but potential driven.

This approach allows us to incorporate directly observable interaction in a very simple way. Once we have achieved an at least intuitive match with governing aspects of crowd motion while keeping the computational cost low, the question of more complete testing and validation remains. We believe that progressive work, such as introducing a group model, should be built on a thoroughly tested basic model. We make sure that when we enlarge the model, we do not lose desired properties by always going through a number of prescribed qualitative and quantitative test scenarios.

In this paper we do not strive to give a complete description of the, very successful, cellular automaton approach based on potential fields. Nor can we cover all of our particular choices of submodels or basic tests.[1] Our goal is to enhance any such model by a vital aspect for useful application suggested by social scientist research: group formation.

Group formation in the cellular automaton model

What is a group? In a first step we need to identify the relevant characteristics that must be captured by the mathematical model to reproduce correctly the geometric cohesion within the groups as well as further typical behaviour of groups. We consider each group as an accumulation of persons who stay together while moving. They move at approximately the same speed towards the same goal. Also, we assume that small groups display certain formations (Qiu & Hu, 2010; Singh *et al.*, 2009). We think that one of the main challenges is to ensure the right type of cohesion: groups, as a whole, must remain very stable, while deformations of groups in time and space must be possible; even losing a group member must be feasible.

In the aggregate pedestrian stream simulator of our previous work, interaction between individuals among each other and with the surrounding world is handled through forces that can be described through potentials. To achieve an efficient implementation that maintains the fast simulation speed, we carry over the concept of potentials to group formation. But we also need to add or alter rules to make individuals recognise the group to which they belong and to treat fellow group members differently from strangers.

A simple group model using forces described by potentials and a basic communication scheme

Behavioural patterns

In this section we describe how we capture flexibility, and at the same time, stability, of group cohesion in one algorithm. We assume that the formation of groups is due to a set of behavioural patterns that must be reproduced by the algorithm. This leads to a list of requirements. With the diversity of group patterns in real life, the requirements are not necessarily fulfilled simultaneously by a real group. Nor is the list complete. However, we think, at least for small groups, that group behaviour may be determined by all the behavioural patterns described in detail below. To achieve these behavioural patterns, our model includes several concepts that we describe in the following subsections. Ideally, they are calibrated to measured data.

- All individuals in the group move towards the same goal.
- The members of a group stay together. Permanent separation of a member from the rest of the group may occur but only in extreme situations.
- All individuals in the group move with the same speed, except for temporal variations caused, for example, by avoiding obstacles and collisions with the rest of the crowd. The variations lead to changes in the spatial shape of the group.
- At each moment, there is an individual who gives orientation to the group. All members of the group follow this person at this particular moment. We call the person the group leader. However, this does not imply that the person has a superior social status or special influence in the group. In fact, the leader role, or rather orientation function, within a group is passed along between group individuals according to rules described below.
- The (cooperative) group slows down when a member stays behind.
- Groups have a basic spatial structure that stays relatively unchanged if walking across a free space, but can be deformed by external influences such as the presence of a crowd or obstacles. Moreover, the shape of a group, such as walking abreast, may be deformed, but will re-establish itself when the external force is removed. For example, a couple walks side by side and only shortly switches to a line formation to go through a small opening.
- We focus on small groups where all members wish to talk to each other with ease. We therefore assume that they favour walking abreast.

No repulsive potential among group members

The first and obvious step towards group formation is to switch off the repulsive forces between the members of a group. In addition, each group member is attracted by the potential of a specific group member, the 'leader'. Also, each group member is attracted by the same target, such as an exit, and assigned the same free-flow velocity.[2]

In a crowd of individuals the free-flow velocity is normally distributed, with for example a mean of 1.34 m/s and standard deviation of 0.26 m/s (Weidmann, 1992). It is not obvious how to assign free-flow velocities among groups. In certain situations, for example, the velocity of the slowest may dominate the group speed. In our research work we are interested in regional evacuation (REPKA, 2010). An experiment was conducted within the REPKA research project suggesting that group speed was not dominated by the slowest member (Gerhardt *et al.*, 2011). Instead, we will assume that the free-flow velocity of groups is normally distributed. However, we would very much welcome the suggestions from the social sciences to improve and ground our modelling work.

As in the model for individuals, group members slow down when they are in a dense crowd. The deceleration depends on the density of the surrounding crowd. Since individuals who are close together experience the same crowd density their tendency to walk at the same speed is enforced. All this allows group members to stay together. With a careful choice of the leader potential—with respect to form and parameters—it is even possible to generate certain group formations, such as walking abreast.

The leader and follower concept

The method is based on an asymmetric group, in which one person is temporarily distinguished from all other members of the same group. This distinguished member takes over the leadership of the group in a certain sense and will be referred to as the leader. The basic idea of a leader has been used in several models for social groups within crowd simulation (Moussaïd *et al.* 2010; Singh *et al.*, 2009). In our model the leader is the member most advanced towards the target. When the leader falls behind he or she can no longer serve as a point of orientation and passes the role on to the new leader. The leader has an attractive potential that affects group members but not strangers. Each follower adds the influence of the leader potential to the sum of all the other potentials that govern his or her decision where to make the next step: the attracting potential of the target, repulsive potentials of obstacles and of strange individuals.

We experimented with several ideas on how to assign the orientation function. At first we used a centre of mass instead of a group member, but without a decision-making entity the group could not decide which way to proceed and sometimes got stuck. Choosing a group member as leader solved this problem. We picked the person ahead of the group, because pedestrians usually look in the walking direction and we presume that, when choosing their path, they orientate themselves towards the fellow group members ahead. In other scenarios, for example, when only one person is well informed about the best path, other assignations of the leader role may be better or necessary. Also, a real group may not always have a leader even in the loose sense used here. However, the model yields very natural visual results (Figure 2).

Communication within the group and the group centre of gravity

Group members are also individuals. They obey the usual rules of motion for individuals unless a group rule overwrites a rule for individuals or completes a rule. So far, we

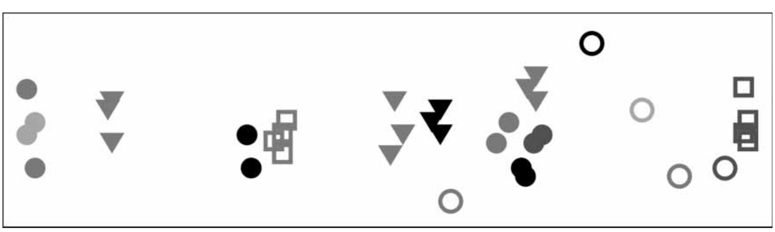


Figure 2. Formation of groups in a computer simulation.

Figure 3. Classroom egress in an experiment.

have not introduced any communication within the group. Left at this stage groups will have a tendency to stay together, but members who had to slow down temporarily, for example to avoid an obstacle or an individual from outside the group, will be lost far too often. Hence we make group members wait for their last fellow. Each group member, including the leader, slows down with growing distance to the last member. This ensures that groups do not gradually drift apart.

In a next step we wish to achieve a certain group formation. The idea is that group members want to talk with each other. Group formations are empirically observed and modelled with fixed attractor points around the leader by Singh *et al.* (2009). Another concept, where a system of differential equations is used to model the communication, was developed by Moussaïd *et al.* (2010). Their model is based on empirical research on group formations and the assumption that people want to communicate within a group. People can talk comfortably only if they do not have to turn their heads backwards or shout to somebody in front. Group members ahead of the group would have to turn their head backwards by a certain angle. They are then told to slow down. Members who trail behind accelerate by a similar mechanism. This means they tend to walk abreast. We wish to adopt these ideas. However, in the cellular automaton, to maintain the automaton's efficiency, one tries to avoid the computationally costly step of solving differential equations. Thus, we look at the behaviour that must be captured and translate it straight into an update rule. In our model, the amount by which they slow down directly depends on the angle. However, the two approaches to express acceleration can be shown to be close in their first-order approximations.

Persons walking abreast and at the same speed are well aligned for communication. Hence they do not adapt their velocity and continue to walk companionably in a way that allows them to talk to each other with maximum ease. Obviously this is a model apt to capture the behaviour of small groups of, say, friends, and not so much large groups or groups with an enforced formation, such as a school class walking in pairs. The authors would like to learn more about which parameters affect the formation of larger groups and how these might split up in subgroups. Also, the authors suspect that the desire to communicate—expressed in the tendency to walk abreast—might be deliberately suppressed by the group members when they face a bottleneck. As a consequence, the communication model can be switched on and off in the computer implementation.

Altogether, in the model presented here, the behaviour of each group member is governed by a balance of mathematically expressed influences:

- Influences that affect each individual: being attracted by a target, being repulsed by obstacles and strangers, and being slowed down by a dense crowd. This leads to a reasonable representation of an aggregated crowd.
- Influences that are caused by being a follower or leader in a group. This entails not being repulsed by fellow group members but being attracted by the leader and, as a consequence, ensures that groups stay together.
- Influences that are caused by an awareness of the other group members. In our model all persons in a group wait for the last member. This part of the model further helps to keep the group together.
- Influences that are caused by communication between group members, that is, by a desire to chat while walking and hence to walk abreast. This means that the group members have to adjust to the rest of the group. The rest of the group is represented by the group's centre of gravity.

Generation of pedestrian groups

In our simulations pedestrians enter a scene coming from a source. At this source the size of a new group about to emerge must be fixed. James (1951) suggests that the members of a group bigger than four are not able to maintain continuous relationships and thus are unstable und divided into subgroups. This might also apply to pedestrian groups. In a later work, James (1953) analyses prior observations of pedestrian group sizes at various places and times. In the data presented 66% of the pedestrians were alone, 34% came in pairs, 7% belonged to a group of three and only 2% belonged to groups of sizes bigger than three. As a concrete distribution of group sizes a zero-truncated Poisson distribution has been suggested (James, 1953; Coleman & James, 1961). The distribution certainly depends on the scenario that is considered. We use a zero-truncated Poisson distribution as default, but the concrete percentage of groups of a particular size can be adjusted according to the scenario.

Visual validation of the simulation

A first step towards validation of a computer model is to compare visually the outcome with expected results. The authors have conducted a series of computer simulations and produced short videos of the resulting pedestrian streams. The snapshot below shows a simulation where groups are generated at one end of a wide corridor (on the left in Figure 2) and walk to the other end of the corridor. Group members show a clear tendency to walk abreast when the path is clear. They temporarily give up that preferred formation when they need to negotiate their path between other groups. This is exactly what the authors want to achieve.

A small experiment: groups matter—but do not necessarily slow down egress

The authors conducted a small experiment with a class of 30 computer science students in their first semester: a very homogenous group of 27 males and three females, all about 20 years old and fit. The objective of the experiment is to provide a test for the validity of our group model. Quantitative tests are difficult to design, because one needs a parameter that can be measured not only in the simulation, but also in reality. We choose the egress time at a bottleneck as experimental parameter, because it is at the same time of vital important for practice. We asked the students to stand at their desks and, at a signal, to leave the classroom. They were not given any instructions on how to communicate—in the hope that they would behave naturally. Outside the classroom, in the hallway, they were asked to turn left and walk across a line between the hallway and the larger entrance hall. The time was measured from the signal to the moment when the last student crossed the line. On the way out there was essentially only one bottleneck: the door.

Then, again at a signal, the students returned from their mostly unchanged positions in the hallway to their assigned seats (without sitting down in order to keep paths relatively free). The time between the signal and the arrival of the last student at his or her place was measured. Here the students encountered three types of bottleneck: the narrowing from hall to hallway, the door, and finally the narrow aisles between the rows of desks in the classroom.

In a second round, the students were paired with their desk neighbours and told to stay together. In a third round triplets were formed. The classroom has rows of desks with eight seats per row, so that some of the triplets were split across rows. The final round was conducted with groups of four. In order to quantify the influence of group size on the egress time, a linear regression was carried out. As expected, there was a positive relationship between group size and egress time, $\beta = 1.16$, ($t(5) = 2.52$, $p = 0.05$) (Figures 4 and 5).[3] The same model is analysed for the ingress scenario. This time the relation was significant but negative, $\beta = -1.59$ ($t(4) = -3.63$, $p = 0.02$).[4]

In both cases we see an impact of groups. The egress result seems intuitively clear from comparison with physical effects: The coarser the grain the more difficult it is to feed it through a funnel. Larger groups correspond to a coarser grain in that picture. With increasing group size, it becomes more difficult to stay together at the door and the overall evacuation time increases. This explanation also agrees well with the personal experience of the authors and, maybe, of some of the readers.

The ingress case is more complicated. Why are the students faster when they form groups? This is not what we expected when we set up the experiment. Let us therefore

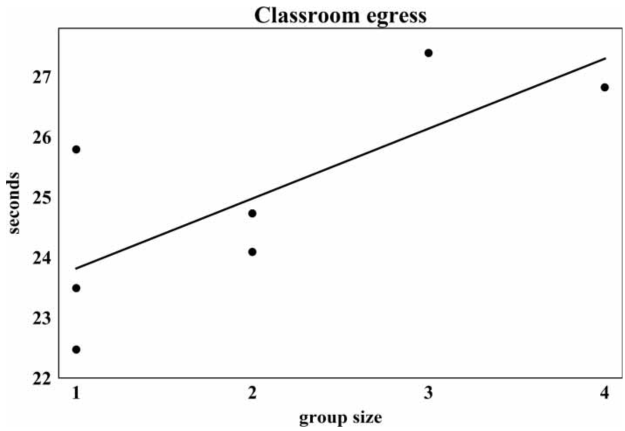


Figure 4. Experiment: dependency of classroom egress time on group size.

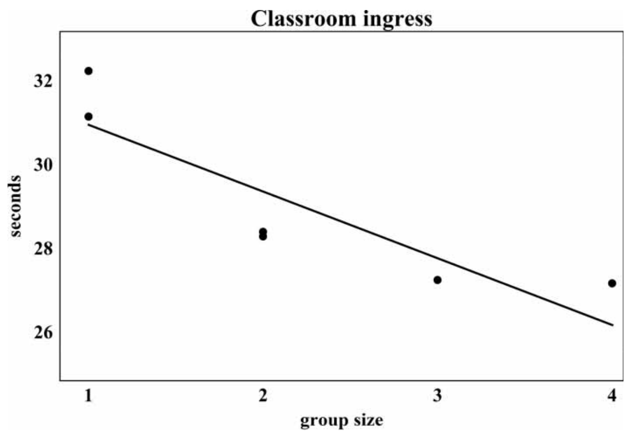


Figure 5. Experiment: dependency of classroom ingress time on group size.

have a closer look at the situation. We believe that the reason for the discrepancy lies in the fact that the students must navigate their way back to their seats. As soon as the students form groups as prescribed in the experiment's choreography, they are already positioned and ordered in the hallway according to the location of their seats in the classroom. This greatly facilitates navigation in the crowd. They no longer impede each other. The organisation is optimal with groups of four, the maximum group size in the experiment.

By these results we are encouraged in our hypothesis, that the occurrence of groups aggravates congestion at isolated bottlenecks and that the impact increases with average group size. But we also learn that against our first intuition groups are not necessarily worse in an evacuation scenario. On the contrary, groups might help. Yang *et al.* (2005) simulated evacuation processes with a different model of interaction. They also found that cooperative interactions of persons among a crowd can result in faster evacuation. Qiu & Hu (2010) simulated crowds with an agent-based model and obtained results that show an increase of flow along with increasing group size in certain situations. Although the mentioned authors present no empirical data to confirm their findings, it shows that these interactions can have a positive impact on the macroscopic outcome of a simulation. We would like to discuss this with fellow scientists from the social sciences, especially since mathematical modellers need not only a collection and classification of possible scenarios, but also must reduce the variety of scenarios to a number that can be handled by computer models.

Simulations experiments and validation against measurements

Pedestrians walking along a corridor

In this simulation a crowd moves along corridors with varying width. The number of persons entering the corridor per time unit is always the same. Thus, the smaller the corridor, the denser the crowd. For each corridor width, the parameter *average group size* is gradually increased from 1, corresponding to an aggregate crowd of individuals, to 4. The simulations results are shown in Figures 6 and 7. We see a strong decrease of the mean velocity with the mean group size. It is evident even in the quasi-free-flow case, suggesting that groups may impede each other, even in the absence of restricting walls, as long as they wish to walk along the same (shortest) path. This is certainly the case in this simulation. The mean crowd density in the corridor (Figure 7) increases with the group size although the same numbers of persons are inserted in the corridor. This is another way to look at the same effect: Groups impair each other's progress, which results in slower progress, and hence congestion. The results of the simulation correspond to our intuition and thus complement the qualitative visual validation of group formation in Figure 2.

Reconstruction of the experiment in a simulation

For every experiment in this section, we ran 1000 simulations where the free-flow velocity is randomly assigned to the groups using a normal distribution as described in the model section.

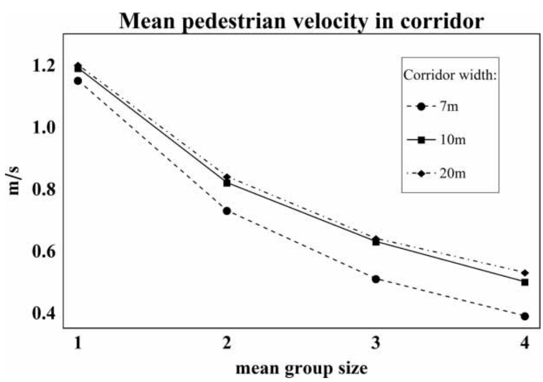


Figure 6. Computer simulation of a corridor: dependency of the mean walking velocity on mean group size.

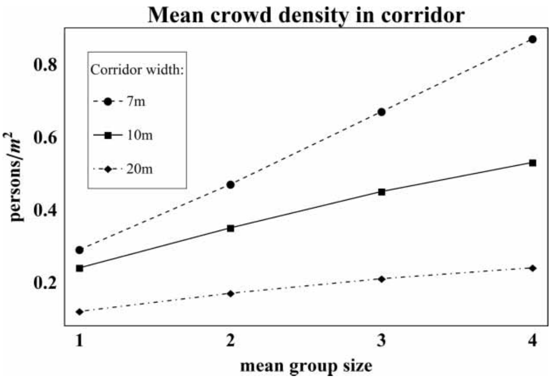
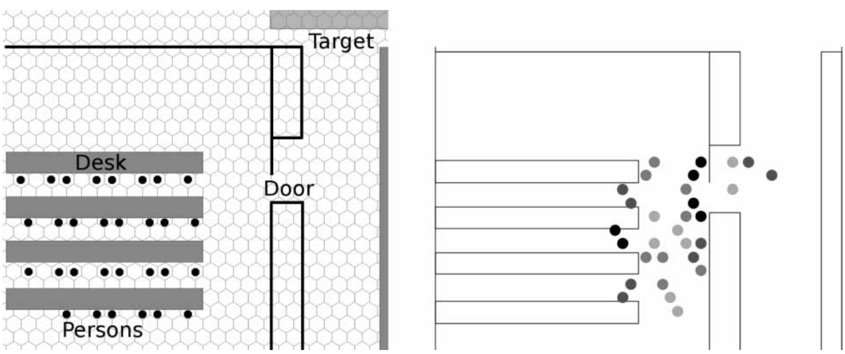


Figure 7. Computer simulation of a corridor: dependency of crowd density on mean group size.

Computer simulation of egress—communication model without calibration. First we present a simulation without attempting quantitatively to match the results. We want to see whether the egress time increases with the group size. For this we generate individuals, pairs and groups of sizes three and four behind the desks, as in the experiment (Figure 8). The egress simulation qualitatively matches the experiment: the bigger the group size, the slower the egress. For individuals the simulated egress time is actually already close to the experiment, indicating that the order of magnitude of the simulation results for individuals is already quite good. This is not surprising since the model has been carefully calibrated for the case of individuals (Davidich & Köster, 2010).

However, the impact of groups is largely overestimated (Figure 9, dashed line). Why is that? We had a closer look at the videos: the students do not appear to talk to each other much while they are queuing—one behind the other—for the door. Since the class is usually a rather lively one, we suspect that the students deliberately suppress their natural penchant for chatting to get through the bottleneck better. The virtual students in the simulation, on the other hand, try to walk abreast (Figure 8). We conclude that our uncalibrated model overemphasises communication.



Figures 8. (left) Geometry of the computer simulation; and (right) snapshot of the computer simulation without calibration.

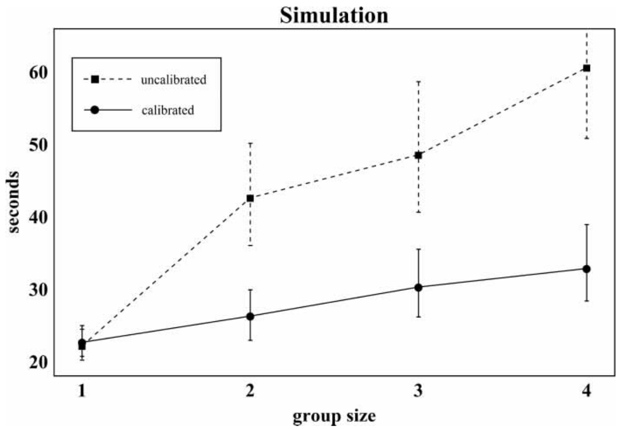


Figure 9. Computer simulation of classroom egress with an uncalibrated (dashed line) and a calibrated (solid line) communication model.

Computer simulation of egress—communication model with calibration. In our uncalibrated model the spatial formation of the group is mainly enforced by group members slowing down to wait and less by group members accelerating to catch up. Hence, in our final simulation we adjust these model parameters with the goal still to make the groups stay together but with a weaker tendency to walk abreast at bottlenecks. For this, we make our virtual leaders wait less and our virtual followers catch up faster. In the visualisations of the simulations we finally observe the desired behaviour: the virtual students stay together—with a tendency to walk one behind the other through the bottleneck and to walk abreast once they reach the hallway. The quantitative results also mirror the experiments.

This is exactly what we hoped for. However, in view of the size of the sample in the experiment one should not over-interpret the results. In particular, one should not fine-tune the simulation parameters against the measurements. Nonetheless the very good reproduction of the experiment strongly encourages us in our belief that our computer model indeed captures the governing characteristics of group behaviour in small groups. To a certain extent it does it even quantitatively. We also conclude that the strength of the desire for intensive communication (chatting) may be the crucial calibration parameter when investigating bottleneck scenarios.

This poses a true challenge to the mathematical modeller and software architect because in a real scenario different types of bottlenecks are common so that it may not be possible to adjust the parameter once and for all. But what is the worth of a calibration that can be used for one scenario only? Obviously, to make the task manageable the number of scenarios must be limited and a common denominator must be found. Insight from the social sciences would be an immense help.

Conclusion

In this article we presented a mathematical model of group formation in a moving crowd based on a cellular automaton. The model incorporates a mechanism that is based on the assumption that pedestrians wish to communicate while walking and therefore prefer walking abreast when the path is free. We demonstrated how far it reproduces reality by validating the model against intuition as well as measurements. We conducted an experiment for classroom egress and compared it with simulation results where we varied the desire for communication. Close inspection of the egress video footage from the experiment showed that the students did not talk much during the egress but tended to walk one behind the other through the classroom door. We concluded that people who navigate a bottleneck as a group temporarily suppress their wish to communicate. We calibrated our model parameters so that the behaviour at the door was reproduced without losing the correct group formation in the free flow. The resulting simulations matched the experiment not only qualitatively, but also quantitatively.

The future challenge lies in better quantifying this effect. When, to which degree and for how long do people give up their desire to communicate in favour of easier navigation? And how do we incorporate the dependency on the 'when', 'where', 'how much' and 'how long' efficiently into a computer model? We will continue our work in this area—and will seek assistance from the social sciences in this endeavour.

This brings us to our second goal: we did not present our work for the sake of the model and simulation results only. We also used it to demonstrate the process of mathematical modelling of crowds to our colleagues from sociology and psychology. One of the major difficulties we faced is that we can only incorporate a very limited number of influences while maintaining computational efficiency. Hence it is crucial to select the governing influences correctly. However, so far this selection has often been based on the intuition of the mathematical modeller, not on accepted sociological or psychological facts. Thus, we also tried to point out where our mathematical formulations lack a scientific foundation from the partner sciences.

Our hope is to trigger more interdisciplinary cooperation in the field of crowd modelling. We believe that the work has just begun. At the same time, the results enjoy considerable public attention making it perhaps even more attractive to join efforts across the usual scientific boundaries.

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Notes

1. For a more detailed description, see Davidich & Köster (2010), Hartmann (2010), Köster *et al.* (2010) and Kneidl *et al.* (2010).
2. Free-flow velocity is the technical term used to describe the speed at which a person likes to walk when their path is free. It is the desired speed of an individual.
3. There is a small-order effect. We introduce *round number* as an additional explanatory variable in the regression model, $\beta_2 = 0.19$, $t(4) = 3.18$, $p = 0.03$.

4. Again the order effect is small. With *round number* as an additional explanatory variable, $\beta_2 = 0.27$, $t(3) = -7.42$, $p = 0.005$.

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