An Agent-Based Simulation of Pedestrian Dynamics: from Lane Formation to Auditorium Evacuation

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ABSTRACT

In this paper we present an agent-based simulation of pedestrian dynamics based on cellular automata models. Differently from the cellular automata, our model represents different pedestrian characteristics: gender, speed, room geometry knowledge, and herding and obstacle avoidance behavior. We study how different room geometries, different pedestrian groups sizes and characteristics influence the pedestrian dynamics and the macroscopic behavior of the system. With this agent-based approach we expect to obtain more realistic results than the cases where the pedestrians are uniformly modeled. Our analysis indicates that pedestrian groups with different features contribute in different ways to the macroscopic behavior.

Categories and Subject Descriptors

I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence
Intelligent agents, Multiagent systems

General Terms

Human Factors

Keywords

Agent-Based Modelling, Pedestrian Dynamics Simulation

1. INTRODUCTION

Modeling and simulating pedestrian dynamics is more complex than simulating vehicles. Computer simulations of pedestrian dynamics are able to show a high number of characteristics that exist in the real world and contribute for a better understanding of basic pedestrian traffic principles. This way, researchers can explore the effects of new traffic rules, changes in rooms geometry and exit paths avoiding dangerous and expensive experiments.

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In classical models such as continuous and cellular automata all pedestrians are modeled uniformly, disregarding notable pedestrian differences. In this paper we propose an agent-based modelling that represents different pedestrian characteristics: gender, speed, room geometry knowledge, herding behavior, obstacle avoidance behavior, etc.

2. RELATED WORK

The three classes of models for pedestrian dynamics – continuous, agent-based, and cellular automata based – represent important pedestrian dynamics features and each has its own characteristics, as well as advantages and disadvantages. In **continuous models** [2], pedestrians behavior is represented by differential equations describing their movement and pedestrian are treated as particles affected by repulsion and attraction forces. This approach is successful when simulating pedestrian dynamics and space-time self-organized patterns, such as lane formations and oscillations on bottlenecks. Regarding **cellular automata models** (CA), in [1] pedestrians have different speeds and are represented by an automata aiming to maximize their frontal movement. In the model by Schadschneider and coworkers (see chapters of Burstedde et all. and Schadschneider in [5]), pedestrians move influenced by a pheromone trail. In **agent-based models** [4] pedestrians are simulated as agents that seek to minimize their mental stress improving their comfort while walking. This last model is the closest to ours in the sense that it is also agent based. However it is less focused on dynamics and more on stress and comfort of the agents, an issue particular to their scenario.

Next we briefly review features such as lane formation, attractive and repulsive effects and make a comment on implementation issues of those models.

Pedestrian flow is more efficient when pedestrians are organized in lanes. Besides, **lane formation** does not arise from the pedestrian initial spatial configuration but is a consequence of pedestrian interactions. Pedestrian dynamics space-time patterns appear due to the non-linear interactions among them. These interactions are caused by model's **attractive and repulsive effects**. Therefore these effects are important to pedestrian dynamics simulation. Attractive and repulsive effects are present in [2]. Pedestrians are attracted to their destination, other pedestrians, or objects. They maintain a certain distance from other pedestrians and objects to avoid collisions. This repulsive effect depends on the pedestrian density and desired speed. The model proposed in [4] has attractive and repulsive effects, represented in the agent's objective of minimizing the *destination* *stress* (*D-stress*), that is the mental stress perceived when the agent cannot go through the shortest way to his destination. Repulsive effect is represented in the agent's objective of minimizing the *pedestrian stress* (*P-stress*), that is the mental stress perceived by the agent from others pedestrians while walking. The model proposed by Adler and Blue represents in the CA rules only attractive effects, but no repulsive effect is simulated. The CA model from Schadschneider and coworkers represents in the *dynamic floor field* and in the *static floor field* attractive effects, however no repulsive effect is modeled.

Regarding **performance**, in continuous models, each pedestrian must be compared with all others in order to perform the attractive and repulsive forces calculation, representing a large effort. In CA models, as they are discrete in time, space, and state variables, plus pedestrian interactions only occur in the local neighborhood, this makes them good for high performance computer simulations such as evacuations of stadiums with thousands of pedestrians. In the model by Osaragi, each agent cannot be too complex, because if it takes too much time to deliberate. Thus, in a simulation with hundreds or thousands of pedestrians the simulation time would be excessively long.

3. MODEL DEFINITION AND DYNAMICS

Our model is based on a CA but represents different pedestrian characteristics. Several underlying concepts are: Preferences Matrix, Floor Field, Sensitivity Coefficients, Speed, Hindrance Coefficient, Transition Probabilities and Collision Resolution.

Each pedestrian Ω has a **preference matrix** M^{Ω} which represents the pedestrian probability of movement in all directions: $\{M^{\Omega}_{i-1,j}; M^{\Omega}_{i,j-1}; M^{\Omega}_{i,j}; M^{\Omega}_{i,j+1}; M^{\Omega}_{i+1,j}\} \in [0,1]$. $M^{\Omega}_{i,j}$ represents pedestrian probability of remaining in his current position. The preferences matrix may be calculated, for example, by a route selection algorithm.

Attractive and repulsive effects are important to reproduce self-organized collective effects in pedestrian dynamics. We avoid explicitly modeling attractive long ranged interactions. Instead, we use the *floor field* concept. Through the *dynamic*, *static* and *repulsion floor fields*, we can simulate pedestrian interactions and attractive geometry effects in a simple and unified way.

The **dynamic floor field** represents the virtual path created by pedestrians while they walk. It models the long ranged attractive interaction among pedestrians. The dynamic field ($D_{ij} = 0$) is zero for all cells (i,j) in the grid at the initial time ($t = 0$). Whenever a pedestrian moves from one cell (i,j) to one of the neighboring cells, the dynamic floor field at cell (i,j) is increased by one: $D_{ij} = D_{ij} + 1$. Besides, the dynamic floor field is time dependent. It has diffusion parameter $\alpha \in [0,1]$ and decay parameter $\delta \in [0,1]$.

The **static field** models space regions that have a higher attractive effect, such as exit doors. It does not change over time, even with pedestrian movement.

The values for the static floor field $S_{i,j}$ used in this paper are calculated as in [3]. The static field has the maximum value at the door cells. It decreases with distance and is zero for the cell farthest away from the door.

The explicit values of $S_{i,j}$ at cell (i,j) is $S_{i,j} = MD - DIST_{i,j}$ with MD being the maximum distance from any cell to a door and $DIST_{i,j}$ being the minimum distance from cell (i,j) to the nearest door.

A pedestrian feels uncomfortable when s/he walks in a strange person's direction. This repulsive effect keeps a pedestrian from getting too close to another person. The original model from Schadschneider and coworkers does not take such repulsive effects into account. The **repulsion field** is our contribution to model the repulsive short ranged interaction among pedestrians. Each pedestrian creates a individual repulsion field. The repulsion field has its maximum value at $E1$ and obeys the relation $E1 > E2$. The resulting repulsion field at position R_{ij} is the sum from all individuals repulsion fields all over the grid and has the following domain: $R_{ij} \in [0, \infty[$.

Each individual in a crowd has a different reaction to long ranged interactions (dynamic floor field and static floor field) and short ranged interactions (repulsive floor field). The model represents each pedestrian in a different way using **sensitivity coefficients**. For each floor field, a sensitivity coefficient is created: $K_s \in [0, \infty[$ is a static floor field sensitivity coefficient; $K_d \in [0, \infty[$ is a dynamic floor field sensitivity coefficient; and $K_r \in [0, \infty[$ is a repulsion field sensitivity coefficient.

Through the sensitivity coefficients, it is possible to model different characteristics such as herding behavior, knowledge about room geometry and obstacle avoidance behavior. For example, a large K_s implies a motion toward the exit via the shortest path. For decreasing K_s a pedestrian performs a random walk and just find the door by chance. This is important for simulations on a dark or smoke-filled room where pedestrians do not have full knowledge about the exit location. The dynamic floor field coefficient K_d controls the herding behavior. A large K_d implies a strong herding behavior, such as the one observed in the panic situation. A full explanation about K_s and K_d may be found in [3]. The repulsion field coefficient K_r controls the obstacle avoidance behavior. A large K_r implies a pedestrian strongly avoidance other pedestrians.

Pedestrians can also have different **speeds**. Differently from [1], the speed values and speed probability distribution are based on real empiric observations about men's and women's speeds. We first generate a Gaussian distribution (mean 1.62 and 1.38 m/s and variance 0.22 and 0.17 for men and women respectively).

During a panic situation, objects that usually hinder the way may be jumped. Chairs, auditorium seats, and other minor objects are common examples. Other models do not take this effect in account during panic simulations. We introduce a **hindrance coefficient** $T_{ij} \in [0,1]$ to represent the possibility of a pedestrian jumping over an obstacle. An obstacle is fully not passable if $T_{ij} = 1$. For decreasing values of T_{ij} it is easier to jump the obstacle.

The **transition probability** P_{ij} to (i,j) for the pedestrian Ω depends on all other concepts presented. With these factors we propose a modified transition probability which is different for distinct situations: normal (Equation 1) and under panic (Equation 2). These formulas are modifications of those proposed by Schadschneider and colleagues and include the repulsion field $exp(K_r \cdot R_{ij})$ to represent the repulsive short ranged interaction among pedestrians, and the hindrance coefficient T_{ij} for panic scenarios.

$$P_{ij} = \frac{N \cdot M_{ij} \cdot (1 - n_{ij}) \cdot exp(K_d \cdot D_{ij}) \cdot exp(K_s \cdot S_{ij})}{exp(K_r \cdot R_{ij})} \tag{1}$$

$$P_{ij} = \frac{N \cdot M_{ij} \cdot (1 - n_{ij}) \cdot exp(K_d \cdot D_{ij}) \cdot exp(K_s \cdot S_{ij}) \cdot (1 - T_{ij})}{exp(K_r \cdot R_{ij})} \quad (2)$$

where N is the normalization factor to ensure that the sum over all the matrix cells is 1 ($\sum_i \sum_j P_{ij} = 1$).

A **collision** occurs when two or more pedestrian choose to move to the same cell. The conflict is solved according to the relative probabilities which each pedestrian chooses the target cell (i, j).

4. SIMULATIONS

Due to lack of space, here we do not show details of all simulations performed (lane formation in a corridor, variable door size evacuation simulation, room evacuation, and auditorium evacuation under panic). Instead, we concentrate on the parameters employed and the results achieved. Mostly, each cell represents 40 x 40 cm^2 and each iteration step is 1 second.

First, one experiment by Schadschneider and colleagues was reproduced for the sake of verification of the correctness of our model. It is the evacuation of a room of 25.2 m^2 or $63X63$ cells, with an exit of one cell in the middle of one wall. All 1116 pedestrians are initially distributed randomly and try to leave the room. It was verified that our results are close to the ones found by Kirchner.

Next, we have performed the simulation regarding lane formation on a corridor (30 X 15 cells) with 65 pedestrians (50% men and 50% women). The dynamical floor field diffusion is $\alpha = 0.05$ and the decay is $\delta = 0.15$. With these parameters, the dynamical field lasts longer and has little diffusion. The repulsion field is: $E1 = 0.6$, $E2 = 0.2$. All pedestrians have herding behavior ($K_d = 1$) and sensitivity to the repulsion field ($K_r = 1$). The kind of experiment can be assessed from the qualitative point of view: our model is able to achieve lane formation (Fig. 1) and pedestrian flow is more organized than a random pedestrian distribution.

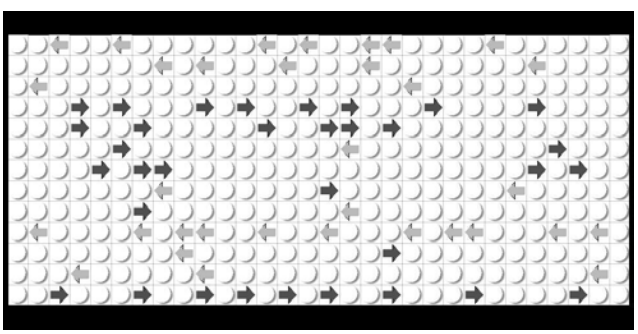

Figure 1: Lane formation

We have then simulated the evacuation of a room, 84.64 m^2 or 23 X 23 cells, varying the door size from 1 to 21 cells. The parameters are $\alpha = 0.05$, $\delta = 0.15$, $E1 = 0.6$, and $E2 = 0.2$. All 132 pedestrians (50% men and 50% women) are assumed to be in the *optimal regime* (they have a combination of knowledge about room geometry ($K_s = 1.3$) and herding behavior ($K_d = 0.5$) that minimizes the evacuation time). The repulsion floor field sensitivity coefficient is $K_r = 1$. We have measured the average pedestrian flow, the evacuation time, and the escape probability. The former increases with the door size (notice that this is not obvious: there are reports showing that pedestrian flow decreases for door size greater than 1 and smaller than 4, when there are conflicts near near the exit door).

In the last experiment, we have simulated the evacuation of an auditorium, 27 X 43 cells, in a panic scenario. The auditorium's chairs have hindrance coefficient $T_{i,j} = 0.9$ and the transition probability in panic scenario is as described in Equation 2. At $t = 0$ there are 237 individuals (50% men and 50% women) distributed in the auditorium chairs. Individuals are in the *disordered regime* after the announcement of a need to evacuate the auditorium quickly. According to [3], pedestrians in this regime are under panic and have a strong herding behavior ($K_s = 0.8$, $K_d = 2$ and $K_r = 1$). The dynamical floor field diffusion is $\alpha = 0.05$ and the decay is $\delta = 0.15$. Pedestrian flow increases at a maximum near time step 50 and begin to decrease near time step 125.

5. CONCLUSIONS AND FUTURE WORK

In continuous and cellular automata models all pedestrians are modeled uniformly, disregarding pedestrian differences. Differently from these, we proposed an agent-based model that represents different pedestrian characteristics: gender, speed, room geometry knowledge, herding behavior, and obstacle avoidance behavior. The motivation to use agent-based approaches is to achieve more realistic results than those from cellular automata and continuous models where the pedestrians are uniformly modeled. Our results indicate that when the pedestrian population is heterogeneous, the macroscopic behavior is different from a uniformly modeled population of pedestrians. Analysis indicate that pedestrian groups with different features (such as the group in the *optimal regime* and the group in the *normal regime*) have different escape probabilities and contribute in different ways to the macroscopic behavior. For future work, we intend to perform simulations with more than two pedestrian groups to investigate how the pedestrian dynamics behavior is affected by mixed classes of pedestrian.

6. REFERENCES

[1] J. L. Adler and V. J. Blue. Cellular automata model of emergent collective bi-directional pedestrian dynamics. In J. S. McCaskill, N. H. Packard, and S. Rasmussen, editors, *Artificial Life VII*, volume VII, pages 437–445. MIT Press, 2000.

[2] D. Helbing and P. Molnár. Social force model for pedestrian dynamics. *Phys. Rev. E*, 51(5):4282–4286, 1995.

[3] A. Kirchner and A. Schadschneider. Simulation of evacuation processes using a bionics-inspired cellular automaton model for pedestrian dynamics. *Physica A: Statistical Mechanics and its Applications*, 312:260–276, September 2002.

[4] T. Osaragi. Modeling of pedestrian behavior and its applications to spatial evaluation. In N. Jennings, C. Sierra, L. Sonenberg, and M. Tambe, editors, *International Joint Conference on Autonomous Agents and Multiagent Systems*, pages 836–843, 2004.

[5] M. Schreckenberg and S. D. Sharma. *Pedestrian and Evacuation Dynamics.* Springer-Verlag New York, Germany, 2002.