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AGENT-BASED APPROACH AND CELLULAR AUTOMATA — A PROMISING PERSPECTIVE IN CROWD DYNAMICS MODELING?*

Jarosław Wąs, Jakub Porzycki, Robert Lubaś, Janusz Miller
Grzegorz Bazior

AGH University of Science and Technology
Faculty of Electrical Engineering, Automatics, IT and Biomedical Engineering
Department of Applied Computer Science
al. Mickiewicza 30, 30-059 Kraków, Poland

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The paper presents recent trends in the area of Cellular Automata (CA) originated microscopic models of crowd. There are many interesting applications of CA-based models, which incorporate different definitions of floor fields, grouping behavior, building complex scenarios, parallelisation of computing processes, as well as the development of validation and verification tests. Thus, due to the observed rapid development of discrete crowd simulation models, they become a real alternative to force-based ones. It is especially visible in a new kind of crowd-model application, where simulation is required to cooperate with different sensors in real-time regime.

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1. Introduction

In recent years, one can observe a sharp increase of interest in crowd-behavior modeling. Different classifications of crowd models are applied in practice, however, the most important classification distinguishes between microscopic and macroscopic approaches. On the one hand, the macroscopic approach is based usually on (nonlinear) partial differential equations based on the mass conservation law, where no individuality is taken into account. Pedestrians are represented by locally averaged crowd density and mean velocity. Interactions between pedestrians are usually represented as closure relations for the average velocity of individuals in terms of the density and its gradient (*e.g.* [1]).

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On the other hand, the microscopic approach is based on the individual motion of particular pedestrians. Thus, in fact, each microscopic model of pedestrian dynamics can be classified as agent-based. Among the agent-based models, two approaches seem to be the most popular: continuous Social Force Model [2] and Cellular Automata (CA) [3], however, one can identify also approaches known from *Game-dev* technology and other.

In this paper, we would like to present a short review on recent trends in CA-based crowd dynamics models. We analyze current trends in CA models (with special attention focused on Floor Field models, that are current, well-established standard) together with validity and performance of this kind of models. As a comparison to CA models, we provide a short description of other microscopic models, namely Social Force Model and virtual crowds from the entertainment industry.

2. Other microscopic approaches in crowd modeling

2.1. Social Force Approach

In contrast to macroscopic models of crowd dynamics, Social Force Models (SFM) emphasize the behavior of individuals, particularly the interactions among them. A pedestrian is subject to three types of forces. The *stimulating force* acts in a desired direction and depends on desired and actual velocity of an individual, the *social force* represents repulsive effects of other pedestrians and borders and, at last, forces modeling attractive effects.

The second term — social force — plays an essential role. In the earliest, classical SFM of Helbing's [2], this term was represented using a concept of a private elliptical sphere of each pedestrian. Such a territorial effect was described by the repulsive potential function of the distance between pedestrians or to a border. In the end, the social force is a distance-dependent function. Yu *et al.* proposed another approach [4]. Their Centrifugal Force Model (CFM) assumed that the repulsive effects between two pedestrians (or a pedestrian and an obstacle) depend not only on the distance between them but also on their relative velocity. It is shown that CFM is capable to reproduce such self-organization phenomena as a lane formation (also in lower — than realizable using classical SFM — ranges of crowd density) and arching and clogging at exits.

Chraibi, Seyfried and Schadschneider [5] proposed a Generalized version of the Centrifugal Force Model (GCFM). The CFM [4] was complemented with a collision detection technique which keeps pedestrians away from each other with a distance not less than the *diameter* of the volume exclusion of individuals. This circular (in CFM) volume exclusion was substituted by an elliptical one. The space requirement of a moving pedestrian depends on his/her speed. This dependency was included for GCFM too.

Although the GCFM is capable to reproduce many of collective phenomena, specialized versions are proposed in particular environments. For example, Saboia and Goldstein [6] consider the low-density flow of pedestrians. They take into consideration the *stimulating force* and (using a mobile grid) redesign it to change the direction of the desired velocity avoiding smoothly blocked or crowded areas. The proposed model — compared to SFM — produces more relevant trajectories, particularly near an obstacles and narrow exits. Another example of relevant SFM modifications is proposed by Johansson *et al.* [7]. They introduced several extensions to improve the treatment of waiting pedestrians.

2.2. Entertainment industry approaches

Crowd simulations applied in games have specific requirements — all calculations and scenes must be performed in real-time simulation using average hardware. On the other hand, the more algorithmic and visual details are incorporated, the better is the final effect. Many researches refer to trade-off between performance and final visual effect. It should be stressed that the most important procedure in validation of crowd behavior represented in such applications is the users' visual assessment. Such applications should be optimized for stability, visual realism, and often support for highly parallel GPGPU execution.

In [8], the concept of *Reciprocal Velocity Obstacles* is introduced. The main contribution of the paper are local reactive collision avoidance patterns. Such an approach makes it possible to provide oscillation-free navigation schemes for agents in a dense, moving crowd. The proposed methodology is based on a relatively simple, continuous force-based model of pedestrian dynamics, including detailed agent–agent and agent–obstacle interactions. More than 1,000 agents were simulated simultaneously using the proposed method.

The collision avoidance issue is also addressed in the following publication, namely [9] where the authors analyze geometrical dependencies in navigation of disc-shaped agents. Finally, they propose an updated version of the collision avoidance model called ClearPath. The proposed polynomial-time algorithm works in 2D motion.

Kulpa *et al.* [10] present a methodology of collision avoidance calculation. Collisions between moving humans are considered — one can speed-up simulation by disabling collisions when it would not be noticed by spectators. In the publication, a level-of-details (LOD) function has been proposed, the function depends on distance from camera, the camera angle and crowd density. The LOD function evaluates for which objects collisions must be calculated and for which it is not necessary without almost any lack of simulation quality.

3. Current trends in CA-based crowd models

The first CA models of crowd dynamics appeared in the late 1990s. In the beginning, pedestrian movement was modeled as lattice-gas. Muramatsu *et al.* [3] defined a model where the pedestrians move on a square lattice, while [11] expanding his model to a hexagonal grid. In such models, pedestrian movement is defined explicitly by transition rules depending on neighbors configuration, therefore, pedestrians types are required (right/left walkers). Also, the possible application of this model is limited to simple geometries. Nowadays, similar approaches are rather rare — used mostly in models designed for specific geometric configurations [12] (*e.g.* movement in corridor).

Currently, the dominant approach for crowd modeling using Cellular Automata is the use of potential fields (see Table I). Such an approach was proposed in [13], two different floor fields were introduced: a static and a dynamic one. The static floor field defines a discrete potential field directing pedestrians towards Points of Interests (*e.g.* exits). The definition of a discrete floor field is based on chemo-taxis-navigation taking into account a trace of predecessors, each pedestrian after the movement leaves a *bosons* that are subject to diffusion and decay. It is worth noting that the paper proposed a current standard size of the grid and pedestrian measuring: 40×40 cm.

Further improvements of the Floor Field were proposed in [14] and [15]. In [15], the authors introduced a *wall floor field* that models repulsive potentials of walls. Moreover, a new method of static floor field calculation with respect to the obstacles was proposed. In [14], the authors consider pedestrians that can move more than 1 cell per step ($v_{\max} > 1$) as well as the effect of finer grid discretization — 20×20 cm. Ezaki *et al.* [16] proposed the application of the *proxemic floor field* as a mechanism of acquisition of space that allows reliable simulation of inflow scenario. In another paper, they applied this model for detailed evacuation analysis [17] and investigation of phase transition from free flow to congestion.

The idea of Floor Field Models has been successfully developed during the recent years. Influence of neighborhood type (von Neumann/Moore) and calculation method of a static floor field (penalty for diagonal movement) on pedestrian behavior was investigated in [18]. The research was extended by Gwizdałła in [19], where he discussed the proxemic-like effects and scaling properties in floor fields models, as well as modifications of static floor fields in the evacuation process.

TABLE I

Overview of selected CA-based crowd dynamics models.

	Lattice	$V_{\max}$	Floor fields	Neighborhood	Update procedure	Time step	Inertia
Muramatsu *et al.* [3] (1999)	square	1	—	von Neumann	random	—	—
Burstedde *et al.* [13] (2001)	square, 40×40 cm	1	static, dynamic	Moore	parallel	0.3 s	yes
Maniccam [11] (2003)	square	1	—	—	random	—	—
Nishinari *et al.* [15] (2004)	square, 40×40 cm	1	static, wall	von Neumann	parallel	—	yes
Kirchner *et al.* [14] (2004)	square, 40×40 cm and 20×20 cm	higher than 1	static, dynamic	von Neumann	random	0.3 s and 0.15 s	—
Varas *et al.* [18] (2007)	square, 40×40 cm	1	static	Moore	parallel	0.4 s	—
Ezaki *et al.* [16] (2012)	square	1	static, dynamic, proxemic	Moore	sequential	—	—
Wei *et al.* [20] (2013)	square, 40×40 cm	1	static, dynamic	von Neumann	—	—	—

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	Lattice	$V_{\max}$	Floor fields	Neighborhood	Update procedure	Time step	Inertia
Wąs and Lubaś [21] (2013)	square, 25 × 25 cm, agents represented by ellipses	1	static, dynamic, wall	Moore	parallel	0.125 s (max)	yes
Vihas [22] (2013)	square	1	static	von Neumann	—	—	—
Bukáček and Hrabák [23] (2014)	square, 50 × 50 cm	1	static	Moore	complex [24]	0.31 s	—
Shimura *et al.* [12] (2014)	square, 40 × 40 cm	1	—	Moore	random	0.25 s (max)	yes
Leng *et al.* [25] (2014)	hexagonal, side = 20 cm, agents are rectangles (57.9 × 33 cm)	1	static, wall, proxemic	—	parallel	1/24 s (max)	yes
Gwizdałła [19] (2015)	square, 40 × 40 cm	1	static	von Neumann, Moore	sequential, random	0.4 s	—
Vizzari *et al.* [26] (2015)	square, 50 × 50 cm	1	static	von Neumann	random	0.33 s	—
Feliciani and Nishinari [27] (2016)	square, 40 × 40 cm	1	static, dynamic, wall, anticipation	Moore	parallel	0.29 s	—

The issue of a proper static floor field calculation method was also investigated in [20]. The authors showed that in the case of large exits, it is necessary to place a pedestrian point of interest (Virtual Reference Point) behind door cells, which significantly improves space utilization for such kinds of scenarios.

One can notice also an upward trend of including agent aspects into CA models. Vihas *et al.* included follow-the-leader behavior [22]. Mobility aspects of aged persons were a subject of extensive research (including video analysis and CA-based simulations) presented in [12]. Feliciani and Nishinari [27] proposed an interesting modification of available positions for pedestrians in situation of clogging. It was designed for high density crowd simulation that uses sub-mesh.

Leng *et al.* proposes in [25] a psychological repulsive force instead a of classical dynamic field and, simultaneously, the application of hexagonal cells instead of square ones. Moreover, in this model, the authors defined a different movement speed for each pedestrian — driven by its movement frequency. A similar idea of adaptive time span in CA models was presented by Bukáček *et al.* in [24], together with the concept of *bonds* — which enables a selection of an occupied cell as a possible target. This model was used by the authors during a discussion on phase transitions in cellular models [23].

Building complex, real-life scenarios and the application of a more accurate representation of pedestrians in CA models were presented in [21] and [28] where the authors proposed an elliptical representation of pedestrians with proxemic-like effects. A comparison between CA-based and experimental results were presented recently by Vizzari *et al.* in [26] and Hrabák *et al.* [29].

It should be stressed, that the CA-originated methods can be easily adapted to sustain massively parallel crowd modeling using GPGPU [30,31]. Moreover, due to its rule-based nature, it is easy to extend those models with new concepts: proxemic-like behaviors (spatial distribution observable during inflow process) [16] or leader following [22].

4. CA models applicability analysis

4.1. Validity

It is worth noting that, while regarding common experimental research, CA-based models are subjects of intensive validation and verification. In [32], the authors investigate *i.a.* the influence of maximal speed on a fundamental diagram shape. Comprehensive discussion on fundamental diagrams sensibility for different parameters in CA-based models is presented in [14]; Kirshner *et al.* show that the shape of the fundamental diagram is strongly dependent on particles coupling to static and dynamics field. Pedestrians outflow is widely used for comparison of simulation results with experimental data. In [33], the authors compare the flow in different width of bottlenecks with experimental data as a part of validation process. Outflow is also used in [34] where simulation results from different models are compared with experimental outflow.

On the other hand, the main documents that define the guidelines for crowd dynamics models are dedicated to continuous models [35, 36]. There is a need to define a set of CA-specialized tests in order to validate these models against its specific errors [37]. The main issue of CA-based crowd-dynamics simulation is related with its coarse space and time discretization. A strictly-defined grid size enforces inaccuracies in the representation of environment geometry. For example, using a standard 40×40 cm lattice, there is no possibility to represent 1 meter wide doors — one has to choose whether to run simulation using 2- or 3-cell wide doors (80 and 120 cm respectively). Coarse space discretization is also responsible for problems with movement isotropy — the shape of the static floor field is affected by type of the neighborhood used in the model (see: Fig. 1).

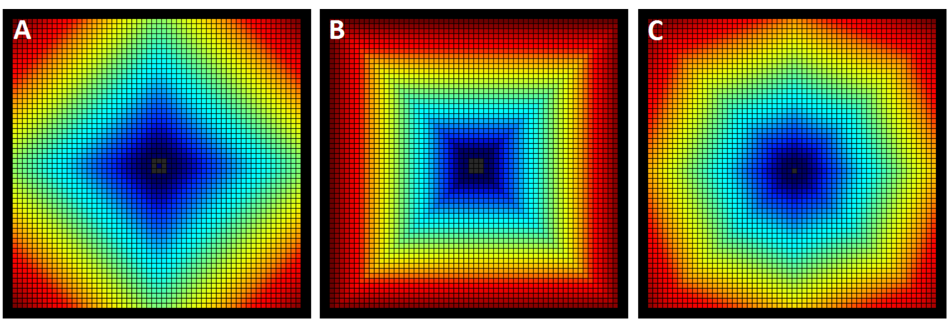


Fig. 1. Static floor field leading to the lattice center generated using different rules. A — von Neumann neighborhood, B — Moore neighborhood, C — Moore neighborhood with $\sqrt{2}$ for diagonal movement.

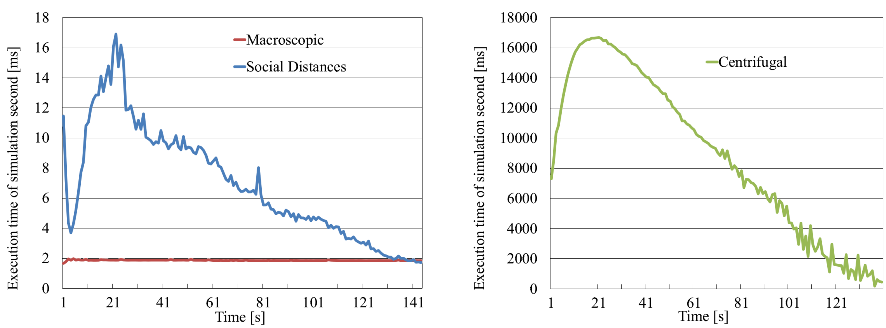
It is worth noting that, currently, there are no CA-based models that can simulate forces between pedestrians, thus their usability to calculate possible threads in high density crowd is limited.

Of course, in comparison with the Social Force Model, the trajectories of pedestrians generated in CA models are more coarse, however the whole method is much more efficient [34] with a good level of reliability. The results of validation and verification presented in many publications [12, 20, 26, 32] show that the method is reliable and appropriate in simulation of different complex, real-life scenarios.

4.2. Performance

Time complexity is very often an important factor for deciding which approach of crowd modeling is suitable. On the one hand, we can obtain results from a more general treatment of the crowd in macroscopic models, on the other, take into account each individual in microscopic models both continuous and discrete one. If requirements of time complexity must fit into real-time regime, the microscopic scale and continuous space probably is not a preferred solution. A better relation between performance and reliability of results have microscopic models based on Cellular Automata. It must be stressed that the performance issues strongly depend on the quality of implementation.

Due to their nature, CA-based models can be easily computed using parallelization. In Fig. 2, we present three representatives of crowd model types — macroscopic, microscopic continuous (Generalized Centrifugal Force model) and microscopic discrete (Social Distance model).



(a) (b)

Fig. 2. Performance tests for all models. The curves show execution time for each consecutive second of simulation [34].

Efficiency was investigated by analysis of execution time of consecutive seconds of simulation. The average execution time-of-simulation second for Macroscopic, Social Distances and Generalized Centrifugal was respectively: 1.86 ms, 6.946 ms, 8825.67 ms [34]. The execution time for macroscopic approach was almost constant for every second of simulation. In the case of the two other methods, execution time-of-simulation second depends on the number of moving pedestrians. The average execution time for the Social Distance Model is of the same order of magnitude as macroscopic model.

5. Conclusions

In spite of the efficiency of the macroscopic methods, they are too coarse to handle complex scenarios for specific facilities. Similarly, methods from the entertainment industry are focused rather on efficiency and overall correctness (that allows generation of spectacular visual effects in real time), than accuracy of the simulation results and model validation. Therefore, we have analyzed some recent publications in the area of microscopic crowd models, especially CA-originated agent-based ones.

Currently, the most popular approach in CA-based crowd dynamics models are Floor Fields. Namely, a transition probability between cells is calculated on the basis of a set of Floor Fields that describes different aspects of cell attractiveness (unattractiveness). Static Floor Field defines the potential that drives pedestrians to attraction points, Dynamic Floor Field is dedicated for following behavior and line formation, while Wall and Proxemic Floor Field introduce a repulsive force from obstacles and other pedestrians, respectively. Some models use also other rules to forbid or allow some movement. In multiple models, the aspects from agent-based modeling are introduced, where each agent may have its own properties and aims, as well as may use different transition rules.

On the one hand, CA models in comparison with continuous, force-based methods, offer only approximated, discretized trajectories of pedestrians. On the other hand, all crucial aspects like flows, densities can be calculated using CA-based crowd models and behavioral schemes of pedestrian dynamics which can be much more complex than in the case of a social force approach. Moreover, due to massive parallelism of CAs, it is possible to simulate wide areas in real-time.

The latest developments prove that many important aspects of crowd simulation, such as: grouping behavior, complex scenarios and psychological aspects can be simulated using CA-originated models. We observe a growing interest in these kinds of microscopic models due to their efficiency and mimicking of complex agents' behaviors using relatively simple rules.

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