Anticipation and Delocalization in Cellular Models of Pedestrian Traffic

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***Abstract*—In this paper an issue of mentality simulation in cellular automata (CA) models of pedestrian traffic is addressed. Anticipation, as one of the major mental properties, plays an important role in behavior of real pedestrians, allowing them to use additional information in a form of sensual perception, knowledge and experience, etc. for optimization of their trajectories. Here we propose an approach to implementation of anticipation property in CA models and discover a relation between anticipation and spatial de-localization of interactions. A number of simulation experiments demonstrated consistency of the proposed approach and revealed some specific features.**

***Keywords*—cellular automata; models of pedestrian traffic; anticipation**

I. INTRODUCTION

One of the numerous applied fields, where cellular automata proved to be an extremely powerful tool, is modeling of pedestrian crowd motion [1], [2]. Having started from quite simple models inherited from physics, researchers are developing more and more sophisticated ones with a trend towards an introduction of mentality accounting into these models [3]. However, such "humanization" of a cellular automaton (CA), that is "mechanistic" by its nature, may demand changes not only in local rules, but also in the structure or in the pattern of interaction of cells. Basic property of a classical CA is locality of all interactions, both spatial (every cell interacts only with several neighbors) and temporal (next state of the CA is determined only by its current state). At the same time, when it comes to simulation of real crowds, this locality assumption is not always consistent, as pedestrians can somehow be informed about the situation beyond their immediate neighborhood (e.g. from visual observation or from notification systems). They can also use this information to predict the situation for several steps ahead and use these forecasts for optimization of their trajectories, a phenomenon, usually referred to as "anticipation" [4], [5]. Thus, the next step in development of the model is its de-localization, i.e. construction of a system lying in-between completely localized system (e.g. CA) and completely decentralized system (e.g. ANN[1]).

II. A BRIEF DESCRIPTION OF THE BASIC MODEL

All the models presented here are based on a CA discrete in space and time. Thus, the model is [3]:

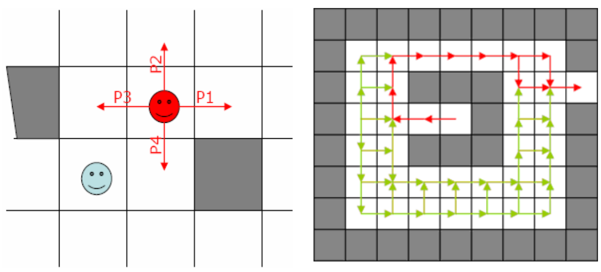
- microscopic: every pedestrian is simulated by a separate cell;
- stochastic: local rules contain random values;
- space- and time-discrete.

The basic assumptions behind the model are:

- dynamics of pedestrian motion can be represented by a CA;
- global route is pre-determined;
- irrational behavior is rare;
- persons are not strongly competitive, i.e. they do not hurt each other;
- individual differences can be represented by parameters determining the behaviour.

A CA has two layers (Fig. 1). The first one – data layer – embeds the information about the geometry of the scene, i.e. placement of pedestrians and obstacles. Every cell in this layer has 3 possible states: "empty", "obstacle", "pedestrian".

The second layer embeds a vector field of directions and stores the information about the global route. This field of



a) b)

Figure 1. Structure of the model

[1] ANN – artificial neural network

directions is constructed so that to minimize evacuation time of a sole pedestrian. If there are several possibilities at a particular point, they are considered to be equally probable.

At every time step, for every pedestrian probabilities of shift for all the directions are being computed according to the following principles:

- if a target cell is occupied (by obstacle or other pedestrian), the corresponding probability is set to 0;
- pedestrians try to follow the optimal global route.

At every step the order of pedestrians' shifts is randomly chosen. Persons differ in their maximum speed. These differences are implemented via division of every time step into $V_{\max}$ sub-steps $t_0..t_{V\max}$. An i-th person tries to move at a sub-step k only if $v_i<k$, where v_i – his maximum speed.

III. ANTICIPATING PEDESTRIANS

Starting from the described above basic model, a pedestrian, capable of foreseeing the situation within his neighbourhood and accordingly optimizing his movement, may be generated. Further, a pedestrian possessing this property will be referred to as anticipating pedestrian.

As it was mentioned above, at every step a person determines probabilities of shift (P_k, k=1,2,3,4). These are these values that may be subjected to influence of anticipation. Let's assume, that pedestrians try to avoid collisions, i.e. a person tries not to move into a particular cell of his neighbourhood if (as he predicts) it will be occupied by another person at the next time step. This may be achieved by changing the probabilities in the following manner:

$$P_k \to P_k \cdot (1 - \alpha \cdot P_{k,occ}), \quad (1)$$

where α – free parameter expressing influence of anticipation, $P_{k,occ}$ – probability of occupation of k-th cell in the neighborhood by one of the neighbors. It is quite natural, that values P_k have to be normalized, so that their sum =1 (if at least one of them >0). It should be mentioned, that in this case all the pedestrians are assumed to have equal rights. If α is set to 1, a situation, when two pedestrians attempt to let each other move and stand still, may occur. Such deadlocks can be completely excluded only by selecting the value of α less then 1, however, the number of them can also be minimized by granting certain (e.g. fast-moving) pedestrians privileges. In this case the shift probabilities will be transformed into:

$$P_k \to P_k \cdot (1 - \alpha \cdot (1 - \frac{v}{v_{\max}}) \cdot P_{k,occ}). \quad (2)$$

It means that the fastest pedestrians do not take care of others, while slowly moving ones try to make way for those moving faster. By using in (2) a somewhat greater value instead of $v_{\max}$, the fastest pedestrians may be forced to be more "polite".

As it was shown above, anticipation is closely related to ability of foreseeing the system state, so the issue of how do the pedestrians predict (in other words, how do they compute $P_{k,occ}$) remains open. Two variants were considered: observation- and model-based prediction. The first variant is based upon the assumption that pedestrians preserve direction of their movement. So, $P_{k,occ}$ may be considered to be a linear function of the number of pedestrians "looking" at the k-th cell (the direction of their look is defined by the direction of their previous shift):

$$P_{k,occ} = \frac{m}{M}, \quad (3)$$

where m – number of pedestrians "looking" at k-th cell; M = <number of cells in the neighborhood>-1, in our case M = 3.
Such an approach, though being the most simple and natural, is, at the same time, the least accurate. Thus, for the sake of comparison, the second approach was considered, according to which a target pedestrian for every cell of his neighborhood computes P_k of its neighbors (excluding himself) and the resulting probability is defined as follows:

$$P_{k,occ} = \sum_{i=1}^{3} P_i - \sum_{i \neq j} P_i P_j + \sum_{i \neq j, j \neq k} P_i P_j P_k. \quad (4)$$

It is quite evident that this approach allows more accurate evaluation of $P_{k,occ}$, while being somewhat unnatural, as every pedestrian must know behavioral models of the others.
A number of experiments were held and typical performance of all the mentioned configurations of the model is given below (Fig. 2).

The results of simulation reveal the fact, that granting fast-moving pedestrians a priority results in greater overall evacuation time, thus making little sense. On the other hand, the more accurately $P_{k,occ}$ are computed, the better the performance. This proves the consistency of the proposed method of anticipation accounting (given by (1)).

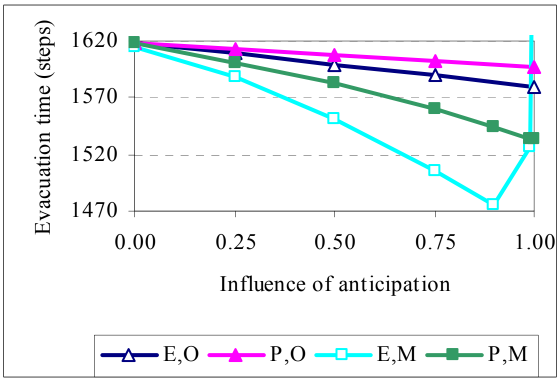


Figure 2. Performance of different configurations of anticipating pedestrians' model. (E/P – equality/priority of fast-moving pedestrians; O/M – observation-/model-based prediction).

IV. SPATIAL "DE-LOCALIZATION"

In the previous section an anticipating pedestrian was generating his prediction based on non-anticipating model of his neighbors. Thus, it is quite straightforward to make his prediction more accurate by involving an anticipating model of neighbors. For that, every pedestrian (within the neighborhood of radius 2) is subjected to the procedure described in section 3 for target pedestrian: calculation of P_k, calculation of $P_{k,occ}$ (4) and correction of P_k (1). It is evident, that in this case cells lying at a distance of 3 from the target pedestrian (center of the neighborhood) are involved in evaluation of $P_{k,occ}$. At the same time, pedestrians standing 2 cells apart from the center used non-anticipating model of their neighbors (standing 3 cells apart from the center). If they have used anticipating model instead, pedestrians standing 4 cells apart from the center of the neighborhood would have become involved. Thus, a neighborhood is growing until it "covers" the entire scene (Fig. 3).

It is clear that this process of neighborhood growth must be interrupted at a certain step, because of two reasons (theoretic and computational):

- every next step destroys spatial localization of the model, thus contradicting the hypothesis of local information (a pedestrian does not know what is happening beyond his neighborhood);
- growth of the neighborhood makes the model more computationally intensive.

Time-cost of calculation of probabilities P_k for one pedestrian is defined by the number of cells in his (extended) neighborhood. In our case (4-cell elementary neighborhood) this number makes up:

$$(r+1)^2 + r^2 - 1 \;\sim\; r^2, \tag{5}$$

where r – radius of an extended neighborhood.

So, this radius should be limited by a certain value, through which different extent of information distribution may be simulated. From a point of view of the target pedestrian, this may be given the following interpretation: all the neighbors inside the extended neighborhood are considered to be anticipating, unlike those standing on a border. On the other hand, pedestrians on a border may be also considered to be anticipating under an assumption that there are no

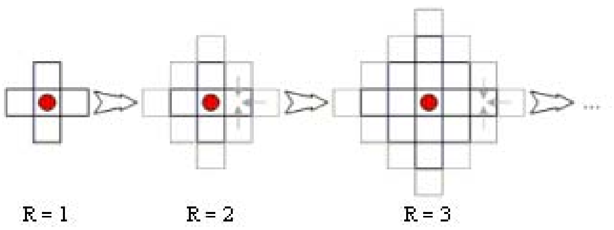


Figure 3. Growth of the neighborhood inducted by anticipating model.

pedestrians beyond the neighborhood (in this case for these pedestrians holds $P_{k,occ} = 0$).

The described above scheme may be implemented via the following algorithm:

<neighborhood initialization:
neighborhood of radius r around the target pedestrian is filled with data from the corresponding area of the CA field>
repeat N times
{
for (all empty cells){
calculate $P_{k,occ}$:

$$P_{k,occ} = \sum_{i=1}^{4} P_i - \sum_{i\neq j} P_i P_j + \sum_{i\neq j\neq k} P_i P_j P_k - \sum_{i\neq j\neq k\neq l} P_i P_j P_k P_l \tag{6}$$

}
for (all pedestrians){
correction of P_k:

$$P'_{k,occ} = \frac{P_{k,occ} - P_k}{1 - P_k} \tag{7}$$

$$P_k = P_k \cdot (1 - \alpha \cdot P'_{k,occ}) \tag{8}$$

}
}

It is quite straightforward, that if r=2 and N=1 we have the model described in section 3 (lowest curve in Fig.2), if r>2 with growing N distant pedestrians start affecting each other, however this influence decreases exponentially with distance. On the other hand, a problem of finding optimal value of N emerges. It is evident, that values less than $[(r+1)/2]$ make no sense, as information spreads with a "speed" of 2 cells per iteration and cells beyond radius of $2N$ are simply excluded from consideration. Also, growing N increases the time-cost of the model (linearly). So, there are two major questions to be answered:

1) will the further growth of N positively affect pedestrians' performance;

2) is there an optimal value of N that provides minimum evacuation time.

In order to answer these questions numerous simulations were held. First of all, we have found that growth of N has a positive effect on the model performance, as it decreases the overall evacuation time (see Fig. 4). However, the slope of the curve decreases in exponential fashion, so, on one hand, there is no definite optimal value (or interval) for this parameter. On the other hand, interval 5..7 seems for practical purposes optimal as further growth of N has little effect.

Secondly, a typical relation between optimal values of α and N was discovered (see Fig. 5).

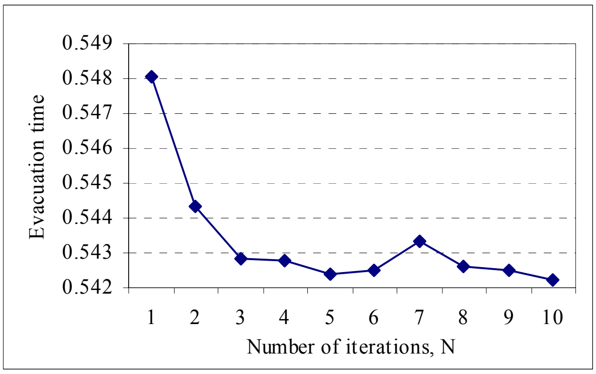


Figure 4. Evacuation time for different values of N. Every data point is obtained for optimal value of α, that depends on N. Evacuation time is given in relative scale with 1.0 corresponding to 150 time steps.

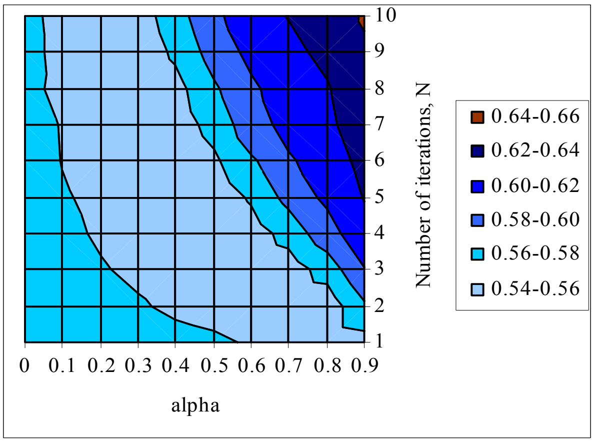


Figure 5. Evacuation time for different values of α and N. Scale is the same as in Fig. 4.

V. Conclusions

In this paper we have incorporated an anticipation property into a CA-based model of pedestrian traffic. It was demonstrated, how this property may be simulated via quite a simple mechanism and what impact it has on the overall performance of the crowd of pedestrians. The one inherent feature of anticipation is a requirement for additional information, based on which a pedestrian tries to optimize his trajectory. As pedestrians move in space, they need to have an idea about what obstacles they will face further on their way. Thus, a need of additional space-related information and, therefore, certain spatial de-localization occurs. In our case, a pedestrian was provided with relevant information via extension of his neighborhood. We have tried providing a pedestrian with another type of information – knowledge about the model of behavior of others. Though not being critical within the described framework, this additional information improved the performance of the crowd.

The approach described allows simulating an arbitrary extent of spatial information distribution by varying the radius of extended neighborhood. At the same time, the model remains localized in time and pedestrians do not make a full use of the additional information they were given. So, the next step in construction of realistic models is implementation of temporal de-localization by granting pedestrians an ability to construct multi-step predictions. However, it is a matter of further research.

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