# Artificial Intelligence of virtual people in CA FF pedestrian dynamics model

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**Abstract.** This paper deals with mathematical model of pedestrian flows. We focus here on an "intelligence" of virtual people. From macroscopic viewpoint pedestrian dynamics is already well simulated but from microscopic point of view typical features of people movement need to be implemented to models. At least such features are "keeping in mind" two strategies – the shortest path and the shortest time and keeping a certain distance from other people and obstacles if it is possible. In this paper we implement mathematical formalization of these features to stochastic cellular automata (CA) Floor Field (FF) model.
**Key words:** cellular automata; pedestrian dynamics; transition probabilities.

## 1 Intoduction

Modelling of pedestrian dynamics is actual problem at present days. Different approaches from the social force model ([1] and references therein) based on differential equations to stochastic CA models (for instance, [3, 2, 9] and references therein) are developed. They reproduce many collective, so to say, macroscopic properties including lane formation, oscillations of the direction at bottlenecks, the so-called "faster-is-slower" effect. These are an important and remarkable basis for pedestrian modelling. But there are still things to be done from microscopic point of view. The better individual pedestrian behavior is more realistic collective interaction and shape of flow are.

We have focused on a fact that in regular situations (non emergent) pedestrians choose their route more carefully [1]. And our aim is to mathematically formalize some features of individual behavior and as a result to improve simulation of individual and collective dynamics of people flow. We focus on implementation to a model such behavioral aspects of decision making process as: pedestrians keep a certain distance from other people and obstacles if it is possible; while moving people follow at least two strategies — the shortest path and the shortest time. Strategies may vary, cooperate and compete depending on current position.

Our model takes inspiration from stochastic floor field (FF) CA model [3] that provides pedestrians with a map which "shows" the shortest distance from current position to a target.

There were introduced [4] already some innovations ("people patience", "visibility radius", "environment analyzer") that allowed to extend basis FF model towards behavioral aspect and make more flexible/realistic decision making process. By this reason model obtained was named as *Intelligent FF CA model*. In this paper we extend previous result and develop further intelligence of virtual people in the sense mentioned above.

The article is organized as follows. In the next section, the problem is stated. In Section 3.1, we describe the model in general and update rules. Section 3.2 contains probability formulas. It is followed by the discussion and the presentation of the simulation results.

## 2 Statement of the problem

The space (plane) is known and sampled into cells $40cm \times 40cm$ in size (it is an average space occupied by a pedestrian in a dense crowd [3]) which can either be empty or occupied by one pedestrian (particle) only:

$$f_{ij} = \begin{cases} 1, \text{cell } (i,j) \text{ is occupied by a pedestrian;} \\ 0, \text{cell } (i,j) \text{ is empty.} \end{cases}$$

Cells may be occupied by walls and other nonmovable obstacles:

$$w_{ij} = \begin{cases} 1, \text{cell } (i,j) \text{ is occupied by an obstacle;} \\ 0, \text{cell } (i,j) \text{ is empty.} \end{cases}$$

Starting people positions are known. Target point for each pedestrian is the nearest exit. Each particle from cell $(i,j)$ can move to one of four its next-neighbor cells or to stay in the present cell (the von Neumann neighborhood = $\{(i-1,j),(i,j+1),(i+1,j),(i,j-1),(i,j)\}$) at each discrete time step $t \to t+1$, e.i., $v_{max} = 1$.

The direction to move for each particle at each time step is random and determined in accordance with transition probabilities distribution and rules.

Thus, to simulate the intelligent people movement (directed with typical features) the main task is to determine "right" transition probabilities and transition rules.

## 3 Solution

### 3.1 Update rules

A typical scheme for stochastic CA models is used here. There is step of some preliminary calculations. Then at each time step transition probabilities are calculated and direction is chosen. If there are more then one candidates to one cell a conflict resolution procedure is applied, and then simultaneous transition of all particles is made.

In our case, *preliminary step* includes calculations of static Floor Field (FF) $S$ [3]. Field $S$ coincides with the sampled space. Each cell $S_{i,j}$ saves shortest discreet distance from cell $(i, j)$ to the nearest exit. It doesn't evolve with time and isn't changed by the presence of the particles. One can consider $S$ as a map that pedestrians use to move to the nearest exit. While calculating field $S$ we admit diagonal transitions and consider that vertical and horizontal movement to the nearest cell has a length of 1; length of diagonal movement to the nearest cell is $\sqrt{2}$. (And it's clear that movement through a corner of wall or collum is forbidden, and roundabout movement only is admitted in such cases.) It is made discreet distance more close to continuous one.

The probabilities to move from cell $(i, j)$ to each of the four nearest cells are calculated in the following way:

$$p_{i-1,j} = \frac{\tilde{p}_{i-1,j}}{N_{i,j}}, p_{i,j+1} = \frac{\tilde{p}_{i,j+1}}{N_{i,j}}, p_{i+1,j} = \frac{\tilde{p}_{i+1,j}}{N_{i,j}}, p_{i,j-1} = \frac{\tilde{p}_{i,j-1}}{N_{i,j}}, \quad (1)$$

where $N_{i,j} = \tilde{p}_{i-1,j} + \tilde{p}_{i,j+1} + \tilde{p}_{i+1,j} + \tilde{p}_{i,j-1}$.

Moreover, $p_{i-1,j} = 0, p_{i,j+1} = 0, p_{i+1,j} = 0, p_{i,j-1} = 0$ only if $w_{i-1,j} = 1, w_{i,j+1} = 1, w_{i+1,j} = 1, w_{i,j-1} = 1$ correspondingly.

We don't calculate probability to stay the at present cell directly. But decision rules are organized in a way that such opportunity may be realized and people patience is reproduced by this means.

**The decisions rules** are [5]:

1. If $Norm_{i,j} = 0$, motion is forbidden; otherwise, a target cell $(l, m)^*$ is chosen randomly using the transition probabilities.
2. (a) If $Norm_{i,j} \neq 0$ and $(1 - f^*_{l,m}) = 1$, then target cell $(l, m)^*$ is fixed.
   (b) If $Norm_{i,j} \neq 0$ and $(1 - f^*_{l,m}) = 0$, then cell $(l, m)^*$ is not available for moving and "people patience" can be realized. For this purpose, the probabilities of cell $(l, m)^*$ and all the other occupied adjacent cells are given for the current position. Again, the target cell is chosen randomly using the transformed probability distribution[4].
3. Whenever two or more pedestrians have the same target cell, we use simple scheme to resolute conflicts [3] [5]. Movement of all involved pedestrians is denied with probability $\mu$, i.e., all pedestrians remain at their places. With probability $1 - \mu$ one of the candidates moves to the desired cell. The pedestrian that is allowed to move is chosen randomly.
4. The pedestrians allowed to move perform their motion to the target cell.

[4] This trick of choosing the current position is provoked by the fact that when moving directionally people usually stop only if the preferable direction is occupied. The original FF model [?] never gives zero probability to the current position, and it may be chosen independent of the environment.

[5] Advanced method is reproduced here [9]. But present research doesn't concentrate on exit problems, we only need to provide flow path through narrow places.

5. The pedestrians that stand in the exit cells are removed from the space.

These rules are applied to all the particles at the same time. , i.e., parallel update is used.

### 3.2 Probability

In stochastic CA pedestrian flow models the update rules preferably answer the question "How" to make movement. The transition probability preferably determines "Where" to move. To simulate the collective pedestrian movement with the realistic shape of flow one should use the "right" probability formulas. To make them "right" means to "remember" that in normal situations people choose their rout following some subconscious common rules (see [1] and reference therein). The rules are: a) pedestrians keep a certain distance from other people and obstacles, and more tight crowd this distance smaller, b) while moving people follow at least two strategies – the shortest path and the shortest time. Thus, mostly in this paper we focus on transition probabilities. And our aim is the attempt of mathematical formalization of the features mentioned above.

In FF models people move to the nearest exit and their wish to move there doesn't depend on current distance to exit. From probability view point this means that for each particle among all the nearest neighbor cells a neighbor with the smallest $S$ should have the largest probability. So the main driving force for each pedestrian is to minimize FF $S$ at each time step. But in this case, only the strategy of shortest path is mainly realized. This results in the fact that in the models people density does not regulate distance between people, and a slight regard to avoidance of congestions is supposed.

An idea to improve dynamics in FF model is to introduce environment analyzer in the probability formula. It should regulate distance between people and decrease the influence of the shortest path strategy and increase the possibility to move to a direction with favorable conditions for moving.

There were attempts already to introduce some environment analyzers into probabilities in stochastic CA models [6], [4]. A model presented in [4] reproduces individual dynamics in a proper way (pedestrian moved using more natural path and avoiding obstacles ahead). But collective dynamics was reproduced properly only in the certain rooms with simple geometry (room with one exit preferably in the middle of the wall; there were no turnings, bottlenecks, obstacles, etc.). A main reason of it was that the environment analyzer was not flexible and spatially adaptive and its weight was considerably less than the weight of the driving force.

In this paper we introduce revised idea of the environment analyzer [4] and make an attempt to mathematically formalize complex decision making process that people do choosing their path.

First, we present the transition probability formula; below, we will discuss it in detail. For example, the probability of movement from cell $(i, j)$ to the upper neighbor is

$$\tilde{p}_{i-1,j} = A_{i-1,j}^{SFF} A_{i-1,j}^{people} A_{i-1,j}^{wall} (1 - w_{i-1,j}). \quad (2)$$

Here

- $A_{i-1,j}^{SFF} = \exp\left(k_S \triangle S_{i-1,j}\right)$ is the main driven force:
  1. $\triangle S_{i-1,j} = S_{i,j} - S_{i-1,j}$;
  2. $k_S \geq 0$ is the (model) sensitivity parameter which can be interpreted as knowledge of the shortest way to the destination point or a wish to move to the destination point. The equality $k_S = 0$ means that the pedestrians ignore the information from field $S$ and move randomly. The higher $k_S$, the better directed the movement.

  Since field $S$ increases radially from the exit(s) in our model, then, $\triangle S_{i-1,j} > 0$ if cell $(i-1,j)$ is closer to the exit than the current cell $(i,j)$, $\triangle S_{i-1,j} < 0$ if the current cell is closer, and $\triangle S_{i-1,j} = 0$ if cells $(i,j)$ and $(i-1,j)$ are equidistant from the exit.

  In contrast to other authors that deal with FF model (e.g., [3], [2], [9]), we propose to use $\triangle S_{i-1,j}$. From mathematical view point, it is the same but computationally this trick has a great advantage. Values of FF may be too high (depending on the space size) and $\exp(k_S S_{i-1,j})$ may be uncomputable. This is a significant restriction. At the same time $0 \leq \triangle S_{i-1,j} \leq 1$, and problem of computing $A_{i-1,j}^{SFF}$ is absent;
- $A_{i-1,j}^{people} = \exp\left(-k_P D_{i-1,j}(r_{i-1,j}^*)\right)$ is factor that takes into account people density in the given direction:
  1. $r_{i-1,j}^\star$ is a distance to the nearest obstacle in this direction ($r_{i-1,j}^\star \leq r$);
  2. $r > 0$ is the visibility radius (model parameter) representing the maximum distance (number of cells) at which the people density and the presence of obstacles influence on the probability in the given direction;
  3. the density lies within $0 \leq D_{i-1,j}(r_{i-1,j}^*) \leq 1$; if all the $r_{i-1,j}^*$ cells are empty in this direction, we have $D_{i-1,j}(r_{i-1,j}^*) = 0$; if all the $r_{i-1,j}^*$ cells are occupied by people in this direction, we have $D_{i-1,j}(r_{i-1,j}^*) = 1$. We estimate the density using the idea of the kernel Rosenblat-Parzen's density estimate ([7], [8]):

     $$D_{i-1,j}(r_{i-1,j}^*) = \frac{\sum\limits_{m=1}^{r_{i-1,j}^*} \Phi\left(\frac{m}{C(r_{i-1,j}^*)}\right) f_{i-m,j}}{r_{i-1,j}^*},$$

     were

     $$\Phi(z) = \begin{cases} \left(0.335 - 0.067(z)^2\right) 4.4742, & |z| \leq \sqrt{5}; \\ 0; & |z| > \sqrt{5}, \end{cases} \tag{3}$$

     $C(r_{i-1,j}^*) = \frac{r_{i-1,j}^* + 1}{\sqrt{5}}$;
  4. $k_P$ is the (model) people sensitivity parameter which determines the effect of the people density. The higher parameter $k_P$, the more pronounced the shortest time strategy;
- $A_{i-1,j}^{wall} = \exp\left(-k_W(1 - \frac{r_{i-1,j}^*}{r})\tilde{1}(\triangle S_{i-1,j} - \max \triangle S_{i,j})\right)$ is the factor that takes into account walls and obstacle:

1. $k_W \geq k_S$ is the (model) wall sensitivity parameter which determines the effect of walls and obstacles;
2. $\max \triangle S_{i,j} = \max\{\triangle S_{i-1,j}, \triangle S_{i,j+1}, \triangle S_{i+1,j}, \triangle S_{i,j-1}\}$,
   $\tilde{1}(\phi) = \begin{cases} 0, & \phi < 0, \\ 1 & \text{otherwise.} \end{cases}$ An idea of the function $\tilde{1}(\triangle S_{i-1,j} - \max \triangle S_{i,j})$ comes from the fact that people avoid obstacles only when moving towards the destination point. When people make detours (in this case, f ield $S$ is not minimized), approaching the obstacles is not excluded.

– NOTE that only walls and obstacles turn the transition probability to "zero".

The probabilities of movement from cell $(i, j)$ to each of the four neighbors are:

$$p_{i-1,j} = N_{i,j}^{-1} \exp\big[k_S \triangle S_{i-1,j} - k_P D_{i-1,j}(r^*_{i-1,j}) - \\ - k_W (1 - \frac{r^*_{i-1,j}}{r}) \tilde{1}(\triangle S_{i-1,j} - \max \triangle S_{i,j})\big](1 - w_{i-1,j}); \quad (4)$$

$$p_{i,j+1} = N_{i,j}^{-1} \exp\big[k_S \triangle S_{i,j+1} - k_P D_{i,j+1}(r^*_{i,j+1}) - \\ k_W (1 - \frac{r^*_{i,j+1}}{r}) \tilde{1}(\triangle S_{i,j+1} - \max \triangle S_{i,j})\big](1 - w_{i,j+1}); \quad (5)$$

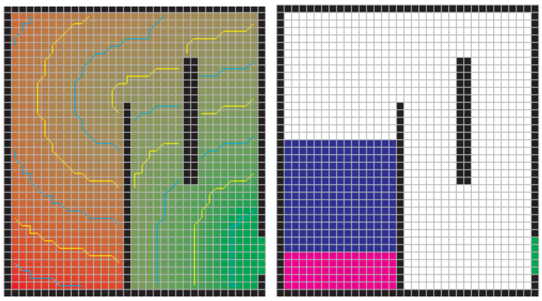
$$p_{i+1,j} = N_{i,j}^{-1} \exp\big[k_S \triangle S_{i+1,j} - k_P D_{i+1,j}(r^*_{i+1,j}) - \\ - k_W (1 - \frac{r^*_{i+1,j}}{r}) \tilde{1}(\triangle S_{i+1,j} - \max \triangle S_{i,j})\big](1 - w_{i+1,j}); \quad (6)$$

$$p_{i,j-1} = N_{i,j}^{-1} \exp\big[k_S \triangle S_{i,j-1} - k_P D_{i,j-1}(r^*_{i,j-1}) - \\ - k_W (1 - \frac{r^*_{i,j-1}}{r}) \tilde{1}(\triangle S_{i,j-1} - \max \triangle S_{i,j})\big](1 - w_{i,j-1}); \quad (7)$$

In expressions (4)-(7), the product $A^{people}A^{wall}$ is the environmental analyzer that deals with people and walls. The following restrictions take place $0 \leq \triangle S \leq 1$, $0 \leq D(r^*) \leq 1$, and $0 \leq 1 - \frac{r^*}{r} \leq 1$. These allows adjusting sensitivity of the model to the people density and the approaching to obstacles using parameters $k_P$ and $k_W$, respectively. To be pronounced people and wall terms should not have parameters less then $k_S$ ($k_P \geq k_S$, $k_W \geq k_S$).

Following the shortest time strategy means to take detour around high density regions if it is possible. Term $A^{people}$ works as the reduction of the main driving force (that provides the shortest path strategy) and the probability of detours becomes higher. The higher $k_P$ the more pronounced the shortest time strategy. Note that low people density makes influence of $A^{people}$ small and probability of the shortest path strategy increases for particle. Parameters $k_P$ allows to tune sensitivity of the model to people density.

Term $A^{wall}$ corresponds only to avoidance of the ahead obstacles so it is not be discussed here. Assume that $k_W = k_S$.



a) Field $S$. b) Initial positions.

**Fig. 1.**

## 4 Simulations

Here we present some simulations result to demonstrate that our idea works. We use one space and compare 2 sets of parameters. Size of space is $14.8m \times 13.2m$ (37 cells $\times$ 33 cells) with one exit ($2.0m$). Static field $S$ is presented in fig. 1a. In Fig. 1b are stating positions of the particles. They move towards the exit with the velocity $v = v_{max} = 1$.

Here we don't present some quantity results and only demonstrate quality difference of flow dynamics for 2 sets of model parameters for model presented.

The first set of parameters is $k_S = k_W = 4$, $k_P = 6$, $r = 10$. The second set is $k_S = k_W = 4$, $k_P = 18$, $r = 10$. Following moving condition are reproduced by both sets – pedestrians know way to exit very well, they want go to exit (it is determined by $k_S$), visibility is good ($r$), attitude to walls is "loyal" ($k_W = k_S$). Only parameter $k_P$ varies here.

If $k_P = 6$ prevailing moving strategy is the shortest path (Fig. 2).

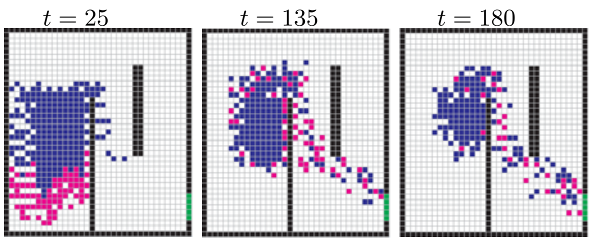



**Fig. 2.** Evacuation for 300 people, $k_S = k_W = 4$, $r = 10$, $k_P = 6$; $T_{tot} = 270[step]$.

The other set of parameters $k_S = k_W = 4$, $k_P = 18$, $r = 10$ (see Fig. 3) allows to realize both strategies depending on conditions and regulate distance between people depending on density.

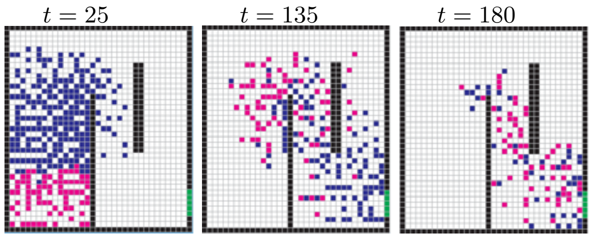



**Fig. 3.** Evacuation for 300 people, $k_S = k_W = 4$, $r = 10$, $k_P = 18$; $T_{tot} = 270[step]$ .

## 5 Conclusion

Under equal movement conditions $k_S = k_W = 4$, $r = 10$ different density sensitive parameters give significant divergence in the dynamics of the model. Combining of the shortest path and the shortest time strategies ($k_P = 18$) gives faster evacuation process, $T_{tot} = 270[step]$ (if $k_P = 6$, when the shortest path strategy predominates, $T_{tot} = 320[step]$), the higher turn radius, the using of detours facilities, the effective use of the exit width, and more realistic shape of flow in a whole. Model dynamics proper needs careful investigation and it is going on. Necessity of $k_P$ spatial adaptation is already clear. It should be a function on space capacity.

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