Simulating pedestrians in evacuation processes: a novel approach

M. Salatino
Department of Territorial Planning, University of Calabria, Italy

Abstract

Pedestrian simulation is a central issue in evacuation related topics; an issue that has recently received renewed interest. In order to estimate escape time from a building, this paper describes a two-module model which combines Agent-Based Models (ABM) and Cellular Automata (CA). The former module (ABM) simulates pedestrians exploring the building space; the latter (CA) simulates the proper evacuation process. The novelty of the model is represented by the first module's approach, which is inspired to Ant Colony Optimisation (ACO). Using this metaphor, it is possible to simulate the way in which people draw their cognitive map of the building's space. According to ACO, agents represent 'scout ants' looking for the exit. Initially, ants move in a random fashion. When an ant reaches the exit, it updates the grid by adding an amount of pheromone. The result is a pheromone trail that follows the shortest possible path from anthill to the exit cell. Running the former module, we obtain a map containing distances from each point to the exit. The latter CA module uses this map to estimate escape time.

Keywords: Cellular Automata; evacuation processes; pedestrian behaviour.

1 Introduction

Simulating pedestrian behaviour can be ascribed to problems dealing with Complex Systems. Everyone has experienced the complexity of pedestrian dynamics: speed slowly decreases as crowding arises, then it drops to zero when density equals a specific critical value. Indeed, jamming formation is due to local fluctuations in pedestrian speed. According to Complex Systems Theory, microscopic events may able to produce macroscopic behaviours, the so-called emergent phenomena. We live through complex systems behaviour every day in a traffic jam, when we stand in a queue or leave a crowded place.

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Since interactions in complex systems usually are not linear, global and deterministic models can fail in foreseeing future status of such systems. In addition, predictions may significantly differ from real measures if not taking into account feedbacks and self-enforcing mechanism of complex interaction.

Because of their great adaptability and suppleness, Cellular Automata (CA) and Agent-Based Models (ABM) have gained popularity among researchers during the last two decades. Using CA and ABM, one can reproduce complex emergent phenomena by enforcing a few simple rules to the model. Moreover, such patterns work very well in simulating self-organising processes in many domains, from biology to traffic control, from social sciences to ethology. Furthermore, the current desktop PC can easily simulate larger crowds and populations. All these strengths moved researchers to test CA and ABM in simulating pedestrian behaviour for safety issues [1–5].

Because simulating pedestrian behaviour involves a large number of variables, studies usually focus on specific aspects of the problem. Some studies [2, 3] concentrate on modelling competitive and co-operative behaviour as in clogging and conflict resolution. Other studies estimate exit rate as a function of door size [4, 5] or of both door size and initial position [6], in order to foresee the formation of arches at the exits. Finally, some studies focus on jammed pattern occurring in intersections of pedestrian flows [7].

In this study, both CA and ABM are used to simulate pedestrian behaviour in emergencies. First, a simple ABM (here agents are 'scout-ants') is used to explore the building, which people are escaping from. Then, an ordinary CA simulates the egress dynamics in order to estimate the escape time. The main goal concerns with simulating the process by which pedestrian collect information about the environment they are escaping from.

2 The model

2.1 General framework

As stated above, we can divide the proposed model into two modules: the former acquiring information about space and the latter simulating evacuation process. These two modules are consecutively performed in distinct steps. Of course, they act on the same representation of the environment, a regular grid-space of squared cells. As in previous studies [2–4], each cell can be either empty or fulfilled by a single agent. When cellular automaton is executed, agent-based model's output (namely the floor field) becomes now an input. In both modules, pedestrians are only allowed to move in four directions, since a Von Neumann's neighbourhood is considered. We are not ruling out resorting to different neighbourhood shapes, e.g. Moore, in further developments. Both in agent-based sub-model and in cellular automaton, cells are updated synchronously.

2.2 The former module: cognitive issues

The novelty of this study is the way in which we consider the distances from the exit. In some pedestrian CA models, information about distance from exit is synthesised in a so-called 'static floor field' [2–4]. Before running the model, researchers usually prepare the floor field by means of euclidean or Manhattan metric.

Such an approach entails two intrinsic disadvantages. First, using this approach in building the surface one obtains the same result whether there are obstacles on the grid or not. Figure 1 shows an obstacle interposing between a pedestrian and the exit. Obviously, every building's floor is a labyrinth full of furniture and partition walls, obstructing and conditioning pedestrian flow. When an obstacle blocks the pedestrian movement, unlike real people shown in Fig.1 (a), Sims could be entrapped in blind alleys, without being able to escape (b). As in most of pedestrian simulating CA, Sims move from high-distance cells to low-distance ones, according to a sort of local search philosophy.

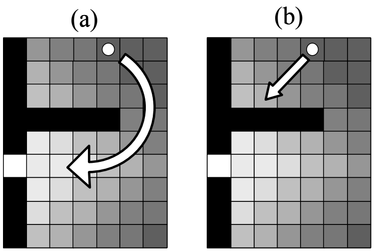


Figure 1: Comparing human and Sim's behaviour in facing obstacles. Local approach entraps the simulated pedestrian in a blind alley.

The second inconvenience is subtler, thus, a change in approach is required to remove it. When we use geometric measures in building impedance surface, we completely ignore the way in which pedestrians perceive space. In modelling pedestrian movement, one must distinguish between actual geometric space and perceived space which are very different. Pedestrians use to refer to the second one, which is not directly measurable since it is a subjective representation of the actual geometric space.

To study the way in which pedestrians move, one must to take into account this cognitive aspect, because people do not measure space by means of an euclidean metric, but they refers to a subjective spatial map in their minds. Environmental psychologists studying these issues usually refer to personal spatial knowledge by means of the term cognitive map. A wide literature has been produced to study spatial cognitive processes, see for example [8, 9]. Cognitive maps are not static, since they continuously grow and become more detailed as person moves. Golledge and Stimson [10] claimed that path or network structure used in everyday spatial behaviour becomes a critical feature in building the personal image of a spatial environment. Indeed, cognitive map formation is a continuous and recursive process, as shown in fig. 2, representing the positive feedback of exploring and acquiring new information about spatial environment.

Exploring the way on which people perceive space is never an easy task for scientists. Horan [11] demonstrated that subjective image of a library varies from a user to another, as anyone can notice by confronting maps, fig. 3.

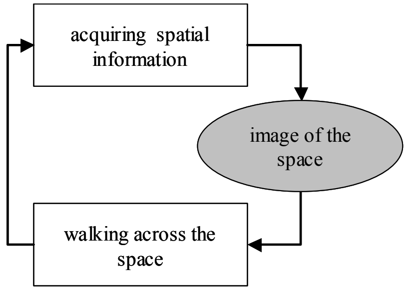


Figure 2: The process of acquiring spatial information.

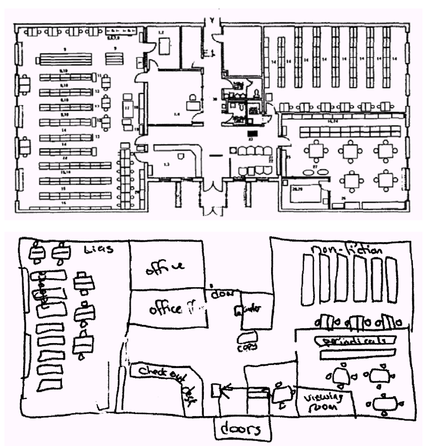


Figure 3: A library and how students perceive it. Sketching is useful in exploring cognitive maps. Adapted from [11].

In order to predict the building users' self-reported incidence of being lost, Weisman [12] measured the readability of floor plans by observing their sketch maps.

Asking people to draw the space surrounding them is the most affordable and effective method for knowing the image of the environment owned by pedestrians. Regrettably, digitising and interpreting sketch maps requires a lot of work as well as hardware made on this specific purpose, e.g. the method proposed by Blaser et al. [13]. Paradoxically, when a rigorous survey of pedestrians' view of the environment is conducted, it takes a chance on putting all researchers' energies into this preliminary stage, rather than focusing on simulation of pedestrian movement.

In this work, we propose a solution by taking in account the cognitive issues stated above and trying to clear the possible hurdles. On the one hand, we attach great importance to cognitive aspects in simulating pedestrian behaviour; to this end, a cognitive-based procedure is implemented to draw the floor field. On the other hand, according to proposed approach, no survey is needed to draw this surface, since an agent-based model is tailored to meet this specific task.

In the proposed solution, agents act like ants in Ant Colony Optimisation (ACO). Although there is no centralised control, an ant colony is able to solve complex problems like treading optimal paths to food. This metaphor is inspired by nature and it is useful in distributed search activities. Ant-based models have been successful applied in many problems of Operational Research, such travelling salesman problem (TSP); see for example [14, 15]. ACO heuristics were first inspired by Chemotaxis, e.g. the biological cell movement induced by chemical substances. This model represents an interpretation of ACO relaxing its principles, since basic aims are different. Indeed, ACO is usually used to search for minimum or maximum. Here, exit location is well known, focal point is now the way to reach it.

In the proposed ant-optimisation model, a swarm of scout-ants explores the grid space. Each scout ant perceives the position of the exit as it is biased by a random error. As a result, ants move in a semi-random fashion. When an ant reaches the exit, it updates the grid by adding an amount of pheromone on the cell it got over. To be exact, ants go backwards from exit to starting point, putting zero in the exit cells, one in the second cells and so on. Obviously, each ant only updates a cell if its value is lower than the cell's current value. This fact could be better represented by means of the pseudo-basic code segment shown in fig. 4.

```
If cell is exit then
    For i = 0 to traveled path length
        If  escape-map current value > i then
            Set escape-map current value = i
        End
    Next i
End
```

Figure 4: The core of the former module. This procedure (here shown in pseudo-code) controls ants in leaving pheromone on the trail they moved on.

Before starting agent-based sub-model run, it is necessary to initialise the escape-map by setting all cells to infinite. Ants are automatically generated in random points of the grid. Moreover, new ants are continuously generated in order to replace those completed their task. Consequently, values in the 'floor field' quickly decrease during the early phases of the simulation, and then they slow down decreasing. Finally, when iteration ends with no more cell updated, simulation stops.

If ants were able to measure distance from exit accurately, they are not able to avoid obstacles, as shown in fig. 1. Thus, ants' sight is biased by random noise. In concrete terms, real distance, say d_r, is biased by multiplying per a random number r.

The result is what ants perceive: d_b, namely biased distance, as in following formula:

$$d_b = r \cdot d_r,\ r \in [0,1]. \tag{1}$$

Each ant moves toward the neighbourhood's cell with the smallest d_b value. As simulation run, ants became able to read the floor field's values, say de. Initially, this characteristic is disabled, since all cells in escape-map have identical infinite value. As simulation run, ants rely more on floor field's values than measured value. Thus, random fashion motion becomes gradually more deterministic. This behaviour is ensured by the following expression:

$$d_p = \alpha(t)d_r + (1-\alpha(t))d_e, \tag{2}$$

where d_p is the perceived distance and $\alpha(t)$ a monotonic increasing function. Initially, $\alpha(t)$ is zero; step-by-step, it rises towards one. Finally, $\alpha(t)$ amount exactly to one when simulation stops. In conclusion, each ant moves toward the neighbourhood's cell with the smallest d_p value. Obviously, ants are not allowed moving toward obstacle cell.

The resulting floor field shows an important characteristic: it might have many local maxima (the obstacles), but no local minimum, since exit is an absolute minimum. This characteristic is vital for the smooth running of the proposed model. Because of it, agents are not in danger of being entrapped in a local minimum. Here, local minimum means that there is no element completely rounded by larger values. Formally, a given a cell so represents a local minimum when:

$$f(s) > f(s_o), \forall s \in N(s_o), \forall s_o \in \Omega, \tag{3}$$

where $f(s)$ is the value in floor field, N is neighbourhood of so and Ω is the escape-map.

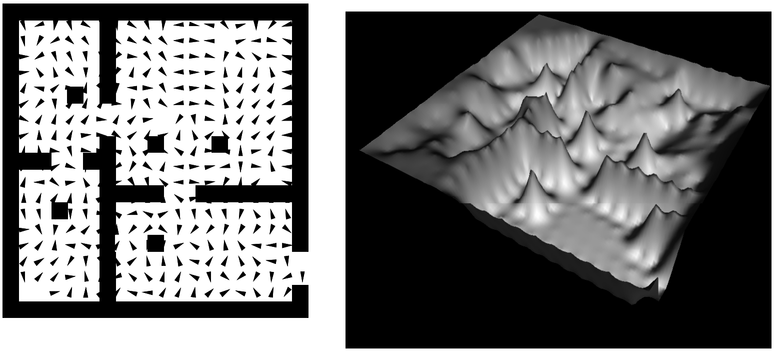


Figure 5: A sample building and the relative floor field as is estimated by the former module. Arrows (left) shows the surface's slope.

It is very difficult giving a rigorously formal proof of this fact, but it could be intuitively understood with the help of a geological similitude. Just to make the things clear, image escape-map initial configuration as a cubic shaped plateau. When rain falls, many little rivers start eroding the rock. After several millennia, the water had scored channels into the plateau, from its centre to the external edges. This metaphor is confirmed observing the continuous representation of the floor field, fig. 5. On the left, a sample building is shown, while the floor field is displayed on the right. Here, black cells represent walls and obstacles, while arrows indicate floor field's slope.

2.3 Cellular Automaton module

Cellular automata are discrete dynamical systems operating on a uniform, regular lattice. According to Artificial Life studies, CA vehicular and pedestrian simulations follow a parallel, distributed and bottom-up approach [16]. Due to many points in common, vehicular and pedestrian CA model evolved parallel to one another. Despite this, modelling pedestrian flows is more difficult than simulating vehicular traffic, because complex adaptive processes affect pedestrian movement much more than drivers. Besides, pedestrian movements are not restricted to canalised lanes, but they occur on a bi-dimensional surface. Finally, pedestrian movements are not encoded by strictly formal rules like signboards or traffic lights.

We opted to design the CA model's structure as simple as possible. Because floor field has been estimated, no more random search is needed and each automaton known exactly where the exit is located. All that automata have to do is to follow decreasing values of the floor field until they reach exit. The resulting movement is a sort of reverse hill climbing similar to local search algorithms. The only difference is that automata look for minimum, i.e. the exit cell.

Since all automata move simultaneously, jamming and arching phenomena are allowed. During every single step, each pedestrian is allowed moving in its neighbourhood, according to two simple transition rules. First, each pedestrian search for minimum escape-map value in surrounding cells included in Von Neumann neighbourhood. Second, if cell with the smallest value is already occupied, automaton stands still.

By fixing pedestrian speed, we are able to estimate the total time to escape. In the last century, a large number of studies have been published in estimating average pedestrian velocity, since this information is of use for many applications. Therefore, range of available data includes many typical values, and then is difficult to decide. In addition, pedestrian velocity is not a constant, because it varies according to sex, age, floor's slope and so on.

We assume that people move at 1.4 m/s, according to Thompson and Marchant [17]. They synthesised data from many studies in a unique curve, according to which, velocity stabilises on 1.4 m/s, when interpersonal distance exceeds 1.5 m/s. In order to estimate escape time, we have to fix cell size too. According to previous studies [x-x], we choose to use a 40 cm x 40 cm grid, which is consistent with ergonomic consideration on average human built. Combining cell size and velocity, results that any time-step last 0.285 second.

Thus, it is possible to estimate escape time by multiplying the number of steps needed to evacuate and duration of a single time step.

3 Simulations

We test the model on a part of a real building, fig. 6, by foreseeing escape time for ten people in two rooms. In order to use the model, we convert this map into the two raster map displayed in fig. 7. The grid on the left is 0.40 metres sized, while the other measures 0.60 metres per cell side.

Black cells are walls and furniture, while grey cells represent chairs, which people start escaping from. Running hundred times the model on both the grid, we obtained the escape time listed in table 1 with the real value in the last row.
As it is to be expected, a finer grid resolution is able to perform better simulations. Moreover, when cell size is too large, obstacles are not well modelled.

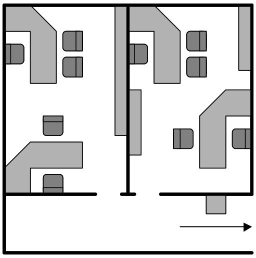
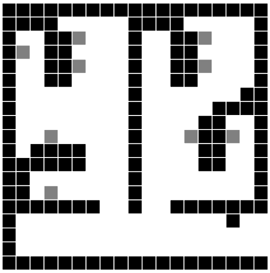


Figure 6: The study area.



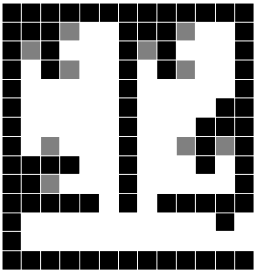


Figure 7: Two raster representations of the study area. A squared lattice with 40cm per size (left) and with 60cm (right).

Table 1: Comparing simulated and real escape times.

	cell size (m)	number of simulation	number of time-steps (sec)	std. dev.	average escape time (sec)
Grid 0.40m	0.40	100	29.2	1.164	8.33
Grid 0.60m	0.60	100	24.8	1.678	10.59
Observed value	-	-	-	-	7.05

4 Conclusions

In this study, a two-dimensional CA is proposed to simulate the evacuation process. Here the model is requested to reproduce complex patterns occurring during the escape from a building, but it is easy to implement for any situation, such as aircrafts [2] or passenger ships [19]. Thus, the first conclusion is that simple cellular automata are sufficient to yield the richness of pedestrian behaviour. That is correct, but it is not the main goal of this study. Indeed, a number of previous studies have already done it. Unlike them, this study focuses the period preceding emergency. During this everyday life, pedestrians are able to learn subliminally the shortest way to escape, in a so-called cognitive process. The main goal of this paper is modelling the way in which people learn exit paths. To this end, a model using 'ants' is presented. It is shown that this method is able to draw a so-called 'floor field' which is essential in simulating evacuation by means of CA models, see for example [2–4]. The entire model is able to approximate the time needed by ten persons to escape from two rooms, since error is reasonably small (about 1.3 seconds).

Obviously, the proposed model is liable to further improvements. For example, the CA module can be enriched by considering conflicts among pedestrians as in [2]. In addition, some improvements are desirable in schematising pedestrian velocity. Finally, it is possible to consider the effect of exogenous variables, like panic, or constraining conditions as in walking through a door, with counter-flow etc., see for example Lee et al. [18].

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References

[1] Dijkstra J., Jessurun A.J. & Timmermans H.J.P., A Multi-Agent Cellular Automata Model of Pedestrian Movement. *Pedestrian and Evacuation Dynamics*, M. Schreckenberg & S.D. Sharma, Springer-Verlag: Berlin, pp. 173-181, 2001.

[2] Kirchner A., Klüpfel H., Nishinari K., Schadschneider A. & Schreckenberg M., Simulation of competitive egress behavior: comparison with aircraft evacuation data, *Physica A*, **324**, pp. 689-697, 2003.

[3] Kirchner A. & Schadschneider A., Simulation of evacuation processes using a bionic-inspired cellular automaton model for pedestrian dynamics, *Physica A*, **312 (1-2)**, pp. 260-276, 2002.

[4] Burstedde C., Klauck K., Schadscheider J., & Zittartz J., Simulation of pedestrian dynamics using a two-dimensional cellular automaton, *Physica A*, **295**, pp. 507-525, 2001.

[5] Tajima Y. & Nagatani T., Scaling behavior of crowd flow outside a hall, *Physica A*, **292**, pp. 545-554, 2001.
[6] Takimoto K. & Nagatani T., Spatio-temporal distribution of escape time in evacuation process, *Physica A*, **320**, pp. 611-621, 2003.
[7] Muramatsu M. & Nagatani T., Jamming transition in two-dimensional pedestrian traffic, *Physica A*, **275**, pp. 281-291, 2000.
[8] Kitchin R.M., Methodological Convergence in Cognitive Mapping Research: Investigating Configurational Knowledge, *Journal of Environmental Psychology*, **16**, pp. 163-185, 1996.
[9] Lynch K., *The Image of the City*, MIT Press: Boston, 1960.
[10] Golledge R. G. & Stimson R., *Spatial Behavior*, The Guildford Press: New York, 1997.
[11] Horan M., What Students See: Sketch Maps as a Tool for Assessing Knowledge of Libraries, *Journal of Academic Librarianship*, **25(3)**, pp. 187-201, 1999.
[12] Weisman G., Evaluating architectural legibility: wayfinding in the built environment, *Environment and Behavior*, **13**, pp 189-204, 1981.
[13] Blaser A.D., Sester M. & Egenhofer M.J., Visualization in an Early Stage of the Problem Solving Process, *GIS Computer & Geosciences*, **26(1)**, pp. 57-66, 2000.
[14] Dorigo M., Maniezzo V. & Colorni A., The Ant System: Optimization by a colony of cooperating agents, *IEEE Transactions on Systems, Man, and Cybernetics–Part B*, **26**, pp. 1-23, 1996.
[15] Dorigo M. & Gambardella G.M, Ant colonies for the traveling salesman problem, *BioSystems*, **43**, pp. 73-81, 1997.
[16] Blue, V.J. & J.L. Adler, Emergent Pedestrian Streams and Cellular Automata Microsimulation, *Proc. of the 80th Transportation Research Board Conference*, Washington, 2001.
[17] Thompson P.A. & Marchant E.W., A Computer Model for the Evacuation of Large Building Populations, *Fire Safety Journal*, **24**, pp. 131-148, 1995.
[18] Lee D., Park JH. & Kim H., A study on experiment of human behavior for evacuation simulation, *Ocean Engineering*, **32**, pp. 931-941, 2004.
[19] Meyer-König T., Klüpfel H., Keßel A., & Schreckenberg M., Simulating Mustering and Evacuation Processes onboard Passenger vessels: Model and Applications, *Proc. of the 2nd International Symposium on Human Factors On Board*, Bremen, Germany, 2001.