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Evacuation simulation supporting high level behaviour-based agents

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Abstract

Computer based models describing pedestrian behaviour in an emergency evacuation play a vital role in the development of active strategies that minimise the evacuation time when a closed area, with a relatively small number of fixed exits, must be evacuated for a large number of people. The proposed model has a hybrid structure where the dynamics of fire and smoke propagation are modelled by mean of Cellular Automata and for simulating peoples behaviour we use Intelligent Agents. Each agent will possess certain psychological, physiological and social characteristics and based on information that is capable of receiving from its sensors, it may perceive what is happening around, and then take a decision that will reflect its ability to cope with the emergency evacuation, called in this work, behaviour. The simulation model consists of two sub-models, called pedestrian and environmental. As part of the pedestrian model, we have prototyped a methodology that is able to model some of the frequently observed human behaviours in evacuation exercises. In order to test the developed behaviours, we choose simple exercises where the model is applied to slightly different situations of an evacuation due to a potential hazard, such as fire, smoke or some kind of collapse.

Keywords: evacuation simulation; emergency evacuation; intelligent agents; behaviour-based architecture; cellular automata

1. Introduction

In the last years, several modelling approaches have been proposed to deal with the emergency evacuations because the prediction of the peoples behaviour is of great public interest. An emergency is an unplanned event with the capability of disrupting operations, causing environmental damage and especially endangering life.

People, who face a situation of evacuation, can react in many different ways. For example, for a given environment, the traces and times evacuation of people familiar with the place and another who completely ignores it,

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may differ greatly, especially in the first minutes of the evacuation considered critical to the success of an evacuation. These different ways of reacting of the pedestrian and its impact at the time of evacuation of a building is the object of study of this work.

The simulation of evacuation of many individuals requires models which nevertheless provide an accurate description of reality. One type of models is the microscopic approach, which allows to investigate the evolution of an evacuation while the model runs.

Within this category there is a diversity of models, among them we have: a) Social Forces Model(SFM) [1], where the pedestrians are treated as particles subject to long ranged forces induced by social behaviour of the individuals; b) Cellular Automata (CA) Model [2, 3, 4, 5] defined as a discrete dynamic system that offers an appealing alternative because its capacity to develop complex behaviours from a simple set of rules and c) Multi-Agent System (MAS) [6, 7], where we explicitly describe the making-decision process of simulated actors at the micro-level and the structures emerge at the macro level as a result of the actions of the agents, and their interactions with other agents and the environment. Models based on the concept of social forces and cellular automata, can represent individuals as basic units of the system but they have the limitation of assuming that the individuals depicted are homogeneous, i.e. their behaviour will be governed by the same rules [8]. In particular, cellular automata allow to generate local and uniform behaviours that resemble the dynamics observed in real processes of fire and smoke propagation. However, these local features were not suitable for representing certain aspects of peoples behaviours that require a more specific and differentiated perspective. We have developed a model where peoples behaviours are modelled by mean of *intelligent agents (IA)* and for simulating the fire and smoke propagation we use CA concept. In the proposed hybrid model, the space is discretised into small cells which have certain dynamic characteristics (e.g. level of smoke or fire) and can either be empty or occupied by exactly one pedestrian. Each pedestrian is an agent that will have its own thread of control and be able to run independently appropriate actions according to their own state, the perceived environment and the messages provided by the system (external stimuli).

An important aspect of our project was the choice of the appropiate agent approach. A deliberative strategy relies on a centralised world model for verifying sensory information and generating actions in the world [9]. The information is used by the making-decision process to produce the most appropriate sequence of actions for the agent. A purely reactive strategy maintains no internal models and performs no search [10, 11, 12]. Typically, they apply a simple functional mapping between stimuli and appropriate responses, usually in the form of a look up in a table or in a set of rules. In [13, 14] was proposed an architecture that falls between purely reactive and deliberative called behaviour-based approaches. We used this type of architecture because it allowed us to express processed further behaviour than those purely reactive. In our model each agent will be determined by their current perceptions and behaviour. This type of system provides solutions in dynamic and uncertain environments, where the agent has only a partial view of the problem. At first, the agent must observe the environment and gather the state of outside world with its inner world. With this information the agent updates its knowledge, analyses the situation and acts running the rules of its active behaviour or changing to a new state (new behaviour).

This paper is organised as follows. Section 2 describes the simulation model. The sub-section 2.1 explains the sub-model called pedestrian (PsM) and addresses the agent architecture adopted in this work. The section 3 explains the implementation of four primitive behaviours commonly observed in emergency evacuation. In section 4 we describe our work with different instances of the problem we are concerned and report the performance analysis of each case. Finally, the section 5 presents the conclusions.

2. Simulation Model

We have developed a simulation model in which all funcionalities needed can be included in this self made simulation environment. The output of the model is flexible and can be used for different kinds of analysis.

The model consists of two sub-models, called environmental (EsM) and pedestrian (PsM). This model along with the computational methodology allow us to build an artificial environment populated with autonomous agents, which are capable of interacting with each other. The Fig. 1 shows the hybrid model.

The EsM, based on CA, describes the spatial configuration of the environment (geometry of space, exit doors, internal barriers, etc.) and models the processes of diffusion of smoke and fire. The cellular space is a finite

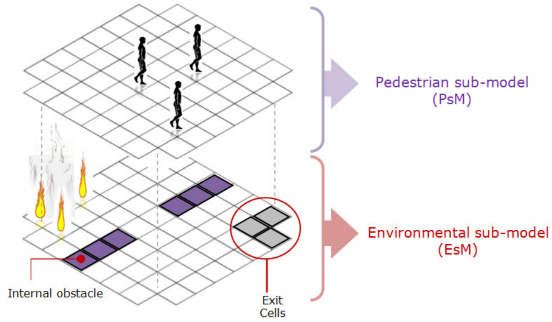

Fig. 1. Hybrid Model consisting of environmental and pedestrian sub-models

bi-dimensional array (grid) with closed boundaries. Each cell of the cellular space represents $40 \times 40\ cm^2$. The neighbourhood considered in the model is *Moore's Neighbourhood*, that includes the eight cells surrounding the central cell. With this choice we aim to provide to each individual in the system with all possible movement directions. The simulation takes an updating time of 0.3 seconds by time-step. This value is the estimated time required by a pedestrian for walking 0.4 m (size of a cell side). For lack of space, we do not extend into the environment model and recommend to see [15] for a more detailed description.

The PsM uses the concept of intelligent agents to describe the cognitive processes of individual agents and interactions among multiple agents in a specific environment. Through interaction and coordinated evolution of these two sub-models it is possible to obtain a model capable of simulating indoor environments with a finite number of outputs that must be evacuated by a group of people due to the threat of fire and the effect of the smoke. The evacuation exercises adopts the CA model for advancing the simulation time.

In the next subsection we extend the pedestrian model, given its relationship with goals of this work.

2.1. Pedestrian Model

Intelligent agents (IA) have been used successfully in a wide range of applications. In artificial intelligence, an intelligent agent is an autonomous entity that observes and acts upon an environment and directs its activity towards achieving goals. The PsM is the part of the hybrid model focuses on representing the human behaviours. In the proposed model an agent is within an environment described by a bi-dimensional grid where they can find different elements such as walls, internal obstacles, exits, presence of smoke, fire and other agents. During the simulation, the environment is presented to the agent as partially observable, stochastic, sequential, and discrete dynamic [16].

The agent architecture is illustrated in Fig. 2. Each agent has a set of psychological (memory and stress level), physiological (age, sex, speed and level of health) and social (level of training and knowledge) characteristics that describe it, which can also be classified as static (age, sex, etc.) or dynamic (level of health, speed, etc.). Besides of all previously mentioned, each agent has a set of sensors which allows it to determine its location, proximity to the heat, the presence of obstacles, distance to known exits, approximate congestion in each exit and detection of signs. As we will explain later in this section, these sensors can be active or not in each agent depending on its current behaviour. An agent can also move in any of eight directions given by the proximity of Moore (actions), i.e. depending on its behaviour, an agent in a central cell can select any of the eight cells in their neighbourhood to move, considering that the movement is validated.

In our model, agents respond to a behaviour-based architecture, this type of architecture tries to compensate for the limitations of purely reactive approaches while maintaining its strengths.

In addition to incorporating some of the properties of the purely reactive systems, these systems based on behaviour enable us to maintain an internal representation of the state of the world that is used in conjunction with the perceptual inputs to determine the action to be performed. Normally this type of system is composed of a collection of behaviours that are more than atomic actions that an agent can make and have the advantage of being able to provide quick responses to dynamic environments [17, 18], allowing also carry out incremental developments and it is relatively simple to implement. Perhaps one of the major drawbacks of this type of system

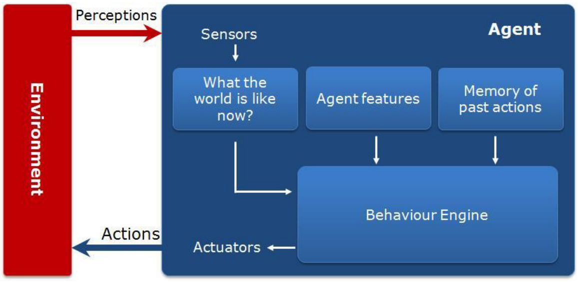

Fig. 2. Agent architecture

is that multiple behaviours with different objectives may be attempting to take control of the agent at the same time. To solve this problem, known as the action selection problem [19], it is necessary to develop a mechanism that allows us to select the appropriate behaviour in a given situation. In our model each agent has an associated behaviour engine that manages decision-making processes. As can be seen in Fig. 3, this engine is a non-deterministic finite automaton, where each node represents the implementation of a behaviour while the transitions represent the event for which the individual can change the state (behaviour). Besides having an original behaviour, during the execution of a simulation, each agent will be associated an active behaviour, i.e. the automaton state associated to the agent during the current simulation step.

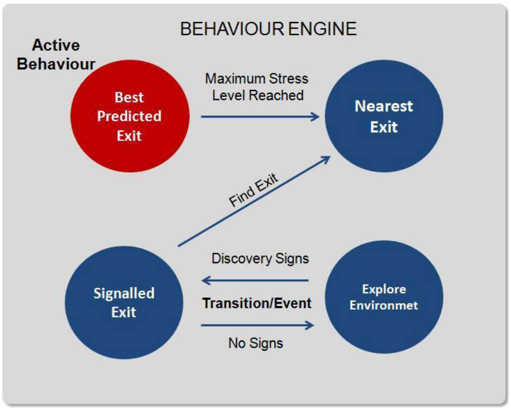

Fig. 3. Example of transitions between nodes in the behaviour engine

Now, the making-decision concerns with combining new facts with existing knowledge for solving different situations. This arbitration state-based mechanism [20], selects an appropriate behaviour to deal with the current situation from a determinate event detected in the environment [19]. In this way, an agent can change its behaviour during execution of the model according to a predetermined set of rules that serve as triggers for this change. For example, an agent unfamiliar with the environment will try to follow the signs placed in the environment to go to an exit. In case the agent could not detect indications in its proximity, it will change its behaviour to explore the environment and will continue in this behaviour up to detecting a sign, moment in which it will take again its initial behaviour to be able to follow it. In this paper, the agent behaviour will be determined by their current perceptions and attitudes of reaction. This type of system provides fast solutions in dynamic and uncertain environments, where the agent has only a partial view of the problem.

3. Primitive Behaviours

In the current state of development, the simulator has the capability to implement three behavioural category. The first category is aimed at testing the behaviour of an individual who has decided to follow the signs as a strategy to leave the place, called *Signalled Exit* behaviour. An agent belonging to this behaviour will obey the signs until leaving the place or some special situation occurs that forces him to make a decision not expected in that category. The second category is designed to test the behaviour of an individual who does not take into account the signs. This behaviour represents environments not signalled, and/or behaviours of individuals habituated to a place. In this category we have implemented two types of behaviours called the *Nearest Exit* and the *Best Predicted Exit* [21]. The last category represents the state of the agent when its strategy, at time, is interrupted by some fact. The behaviour adopted by the agents who are in this situation is called *Explore Environment*.

In the *Signalled Exit* behaviour, the environment is unknown and the path is signalled, i.e. the cell has a sign to indicate the direction to an exit. The agent sees the sign in a cell and moves in direction determined by sign until it finds an exit. The agent could get out of this behaviour by the occurrence of any of the following situations: (a) it can not see any sign; (b) the path to the exit is blocked for the presence of fire, smoke, obstacles, etc. and (c) the agent receives several signs to follow in opposite directions and it has doubt about which path to choose. In any situation, the agent will change its behaviour to *Explore Environment*. The situation (c) can happen when signs are placed too close to each other, overlapping the direction. However, in the case that the signs do not conflict (e.g. go ahead and turn left), the agent will choose randomly between them and continue normally in this behaviour.

In the *Nearest Exit* behaviour, the agent will try to get out the exit closest to its current position. In this behaviour the decision process will take into account the position of the agent, the direction toward the nearest exit, the state of its environment in relation to the progress of fire and smoke, but it ignores information from other alternative solutions, the behaviour of other agents and it will not take unexpected or altruistic decisions. The decision-making process selects the exit with the shortest $PredDist_j$. This measure represents the estimated distance from current position to the exit j.

In the *Best Predicted Exit* behaviour, the agent will analyse different exits and choose one that it predicts the fastest exit to evacuate. The decision process will take into account the position of the agent, the state of its environment in relation to the progress of fire and smoke, the distance to alternative exits, the density of crowd trying to evacuate for each exit (only if the agent can see the exit) and the stress level in relation to its tolerance to it. Under this behaviour, the agent does not follow the actions of others, i.e. remains in the category of individual behaviour but it only checks the orientation of the other agents to choose its way toward the best exit. As the evacuation progresses, the agent is predicting the cost (in time) to evacuate by each of the exits that are available in the environment. The inferred lower cost will indicate the best exit. For that, the decision-making process evaluates the following cost function: $Cost_j = MinPredTime.To_j * PredDist_j * I_j$; if $MinPredTime.To_j >= EvacPredTime_j$. In other case, $Cost_j = EvacPredTime_j * MinPredTime.To_j * PredDist_j * I_j$.
where:

- I_j represents the estimated number of agents who intend to evacuate through the exit j;
- $EvacPredTime_j$ represents the evacuation estimated time of exit j. This factor takes into account the intentions of other agents to escape by the door j;
- $MinPredTime.To_j$ represents the minimum estimated time needed by the agent to reach the exit j considering a free path (unobstructed) and
- $PredDist$ represents the estimated distance from current position to the exit j. This calculus is made using the Dijkstra algorithm.

Note that for the case where $MinPredTime.To_j >= EvacPredTime_j$ it does not take into account the value of $EvacPredTime_j$, because if the spent time by the agent to reach the door "j" is greater than the time taken to dislodge the door, then when the agent arrives at the door, it would find it empty.
In this behaviour, there are three parameters that control the behaviour of an agent: the re-evaluations number that the agent can perform ($EvaluationN_i$), the elapsed time between each one of these re-evaluations ($ElapsedT_i$) and the stress level of the agent ($StressL_i$). The value of $EvaluationN_i$ controls the quantity of times that the agent i can observe the environment and decide which exit is better for evacuating, changing or not its previous decision. The objective of this parameter is to prevent the agent from falling into a state of permanent indecision. The $ElapsedT_i$ controls the amount of time-steps that must occur until the agent i can perform its next re-evaluation. The combined use of these two parameters enable us to investigate what happens with the agents if the same take more or fewer decisions by varying the time between each one of them. Previous empirical results show that a shorter time between re-evaluations works better for small environment, since the evacuation process is faster and

therefore it requires that the agent has the ability to change its decision rapidly. The parameter $StressL_i$ will be increasing as the model evolves and it is responsible to act as a trigger for a change of behaviour. For the case where $StressL_i > HighestStressL_i$(Maximum stress level), the agent i in *Best Predicted Exit* behaviour must change to *Nearest Exit* behaviour. With this change of behaviour we intend to model the situation where an agent due to its stress level stops evaluating the different options that the environment offers and decides to head toward the nearest exit. The resulting procedure instructs the agent which exit to go. This parameters limits the effect of indecision of the agents that occurs when simultaneously multiple agents make the same prediction of fastest exit to evacuate.

Finally, *Explore Environment* represents the state of agents who do not know either an objective exit or its next position in a signalled environment. Its intuitive action is to keep moving until finding an exit or an event happens changing its behaviour. To decide where to move, the agent can use the information stored in its memory enabling it to remember the path followed by the latest movement. The probability of returning to the original behaviour decreases as the simulation progresses.

3.1. Path to the Selected Objective

Each agent knows the objective, either its exit door or its next position in a signalled environment. Based on the perception of its environment, the agent must select at each time step, a position on the path to its objective.

If in the neighbourhood there are free cells that come near the objective, the agent will choose the one that most benefits grants (leave it closer). If there are more than one, the choice of the position is random. If in the neighbourhood there is no free cell, following the approach described above, the agent will select a cell that is currently occupied by another agent. This can cause multiple agents trying to occupy the same physical location belonging to an exit way. To solve the problem, after the agents expressed their desire to move to *the nominated cell*, they should delay their movement until a conflict resolution process is executed. To solve the collisions we changed the approach commonly used: instead of being the agent who decide, the selected cell is carrying out the agents competition process. The hosting decision is concentrated in each nominated cell.

The conflict resolution process must solve two types of situations:

- The conflict occurred when multiple agents chose *the same free cell*. In this case the process gives priority to the selection of agents with greater speed and fewer points of damage (agent parameter). If the conflict persists, the selection will be random.
- The conflict occurred when multiple agents requested *a cell occupied by another agent*. The process must check if the cell will be free in the next time step. If it will be free, the procedure of the same free cell is executed. Otherwise, the agent will not move from its current cell.

In spite of failing to advance in the desired direction, it is reasonable to keep moving until some way towards the objective is found. For this reason, it is important to point out that after a prudential time, if an agent remains without advancing, it will try to move to any neighboring cell although, for the time being, it moves away from its objective.

4. Test-Case Scenarios and Results

The experiments were carried out with EVAC Simulator [2], an integrated simulation system. EVAC is a system developed in Java that allows the design and simulation of spatial environments in an explicit way. EVAC simulator offers a friendly graphical interface which can be easily used by non expert users.

We performed a series of experiments in order to test the behaviours we study focusing on showing the results of the interaction of the two sub-models.

We consider four types of individuals, everyone associated with different behaviours: A_{SE} for *Signalled Exit (SE)*, A_{EE} for *Explore Environment (EE)*, A_{NE} for *Nearest Exit (NE)* and A_{BPE} for *Best Predicted Exit (BPE)*.

With the purpose of obtaining acceptable statistical data, the results shown in all cases correspond to the average of 50 independent replications of each experiment. The corresponding confidence intervals were obtained, for the total evacuation time (TET) (seconds), mean evacuation time (METxA) (seconds) and mean travelled distance (MDxA) (meters) per agent to the exit. $\#E_i$ indicates mean the number of pedestrian exiting door E_i.

In the first set of tests, an environment of 10 x 20 m^2 with 104 individuals (A_{SE}) and two exits are considered: the emergency exit, E_1 of 1.2 m. (on the upper right-side) and the main exit, E_2 of 2.4 m. (at the bottom). The environment recreates a cinema with individuals placed in the seats, observed in Fig. 4.

With the aim to study how the system of signs impacts on the environment, the test compares not only a well signalled environment but also a poorly one.

- Case CN_1: the environment is poorly signalled, since there is no sign indicating to the agents the existence of an emergency exit.
- Case CN_2: the signs have been placed correctly, therefore the agents are able to determine the existence of the emergency exit.

Table 1. Cases of study: Signalled Environment

Case	TET (sec)	METxA (sec)	MDxA (m)	$\#E_1$	$\#E_2$
CN_1	38.89-39.71	14.34-14.47	17.12-17.28	24.52	79.48
CN_2	20.76-33.92	8.98-9.00	10.70-10.73	40.30	63.70

In our implementation, the radius of vision of agents is specified by parameter. In both experimental cases, the agents are outside of the specified radius and therefore when the simulation begins, the agents can not see signs in their closeness. The behaviour engine associated with each agent solves this situation changing its state. So, agents change their original behaviour to explore the environment in order to locate the sign to guide them toward the exit, that is, the agents A_{SE} behave like agents A_{EE}. At the time the agents visualise a sign, they return to their original behaviour. As we can see in the Table 1, the number of people who were evacuated using the emergency exit, E_1, was approximately increased from 25.5% (Case CN_1) to 41.91% (Case CN_2). In addition to, it that is also possible to view that the evacuation times and the average distance travelled to exit have been decreased for the Case CN_2. These evacuation processes can be grafically observed in Fig. 4.

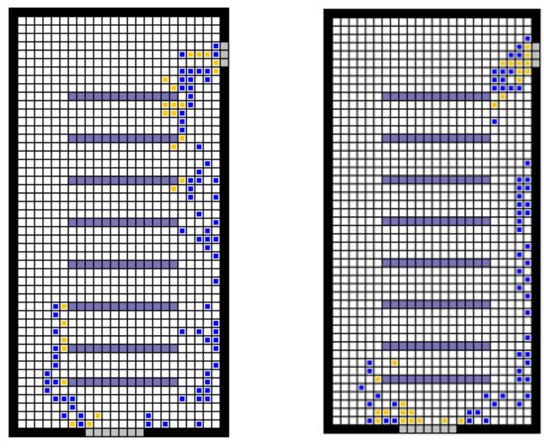

Fig. 4. Snapshot of a simulation at intermediate times: poorly (left) and well (right) signalled exits

In the second set of tests, the environment recreates the post-graduating area of the San Luis Sciences School. It is considered an environment of 40 x 30 m^2 with 610 individuals (randomly distributed) and four exits of 2 m. each one located in opposite ends of the environment: E_1 and E_2 (on the upper and lower right-side); E_3 and E_4 (on the upper and lower left-side respectively). The environment is not signalled (Fig. 5). In the experiments called A and B, we consider that all the people (agents) behaviour should be of type A_{NE} . The Cases C and D are analogous to the previous ones but all the people (agents) behaviour should be of type A_{BPE}. The Cases E and F describe an intermediate situation. It is important to note that in Cases A, C and E, the environment is not affected by the spread of fire and heat, but in Cases B, D and F the agents must adapt to a dynamic environment due to the spread of fire and heat. In these cases, the fire spreads along the corridor and cause that two exits are blocked (E_3 and E_4).

Table 2. 610 agents distributed evenly in the building. 4 Exits.

Case	TET (sec)	METxA (sec)	MDxA (m)	$\#E_1$	$\#E_2$	$\#E_3$	$\#E_4$
A	51.25-51.74	22.41-22.42	26.88-26.89	140.00	164.00	170.00	136.00
B	79.58-80.42	25.79-25.81	30.94-30.96	276.00	334.00	0	0
C	63.82-83.30	26.14-26.26	31.34-31.52	136.94	177.43	163.73	131.90
D	77.20-91.99	30.32-30.53	36.34-36.67	283.25	326.75	0	0
E	54.15-77.94	24.20-24.25	29.01-29.10	136.70	173.40	165.60	134.30
F	80.68-83.64	30.23-30.27	36.27-36.32	274.00	336.00	0	0

The Table 2 shows the result. For the Cases *A* and *B*, the difference observed in the values obtained for TET, METxA and MDxA is due to the appearance of the fire in the vicinity of the exits E_3 and E_4. This situation has as consequence that all the agents, in Case *B*, must evacuate through the exits E_1 and E_2, resulting in an increase in the evacuation times and naturally also in the average distance travelled to the exit, due to the fact that the agents who previously evacuated through the exits E_3 and E_4 they cannot just do it.

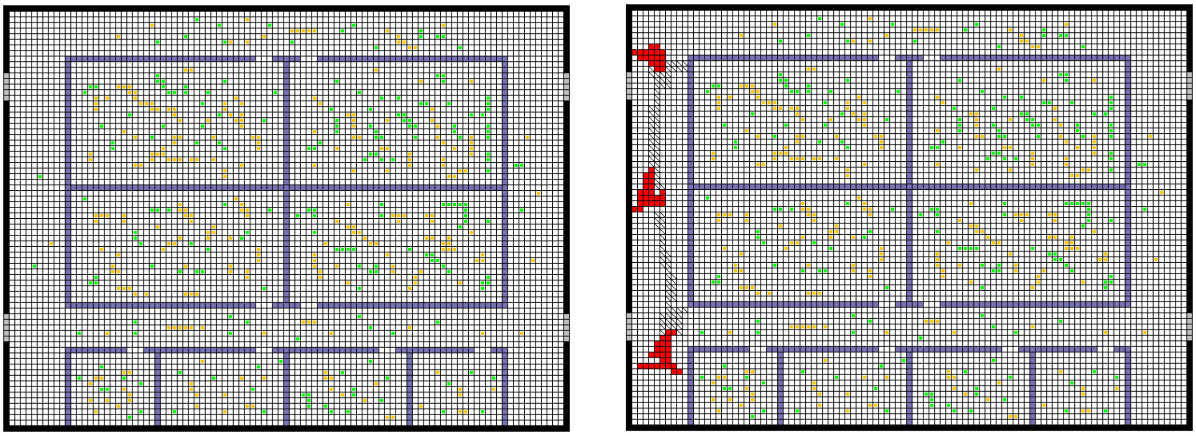

Fig. 5. (left) Case *E*: without fire. (right) Case *F*: with fire (in red). 50% A_{NE}, 50% E_1 for both cases

In an analogous way, the same results can be observed in Cases *C* and *D*, with the difference that all the agents try to infer the fastest exit now. However, the experiments *C* and *D* show TET higher than experiments *A* and *B*. This is because agents travelled a greater distance on average. In the experiments *C* and *D* we observed that many agents, who in the first instance were going to a particular exit, decide to go to other one, since they have been able to detect a less congestion. While it is reasonable to think that agents A_{BPE} should yield better results than the cases with A_{NE}, we were able to observe using our animation tool that agents with *Best Predicted Exit* behaviour generate greater disruption in the environment, with agents who go from an exit to another and even intersect or exceed each other following their path to the exit. This phenomenon can be considered as a type of *emergent behaviour* due to the fact that it arises spontaneously from the interaction of the agents in the environment.

Table 3. A_{NE} and A_{BPE} indicate the type of the agent

—	$\#E_1$		$\#E_2$		$\#E_3$		$\#E_4$	
Case	A_{NE}	A_{BPE}	A_{NE}	A_{BPE}	A_{NE}	A_{BPE}	A_{NE}	A_{BPE}
A	140.00	0	164.00	0	170.00	0	136.00	0
B	276.00	0	334.00	0	0	0	0	0
C	0	136.94	0	177.43	0	163.73	0	131.90
D	0	283.25	0	326.75	0	0	0	0
E	70.00	66.70	82.00	91.40	85.00	80.60	68.00	66.30
F	138.00	135.70	167.00	169.30	0	0	0	0

It should be noted that if the environmental configuration were different or location of the agents were not evenly distributed in the environment, it would be possible to see results opposite to those mentioned above. To verify this situation, please refer to the section *Test-Case Scenarios and Results* of [21].

Finally the Cases E and F show an intermediate situation (Figs. 5 and 6), where half the individuals are A_{NE} and the remaining are A_{BPE}. Comparing the last two tests, as mentioned earlier the values of TET, METxA and MDxA are increased due to the occurrence of fire in the exits E_3 and E_4 (Case F, Fig. 6).

Furthermore, it is also possible to compare the cases A, C and E since they show the same environment without the presence of fire, where what varies is the configuration of the people (agents) in the environment.

Here we can see that as we increase the amount of agents of type A_{BPE}, the phenomenon of disruption in the environment increases, resulting in an increase in the values of TET, METxA and MDxA. The lowest values were obtained for the Case A (100% A_{NE}), while for Case C (100% A_{BPE}) were greatest. As an intermediate situation is the Case E.

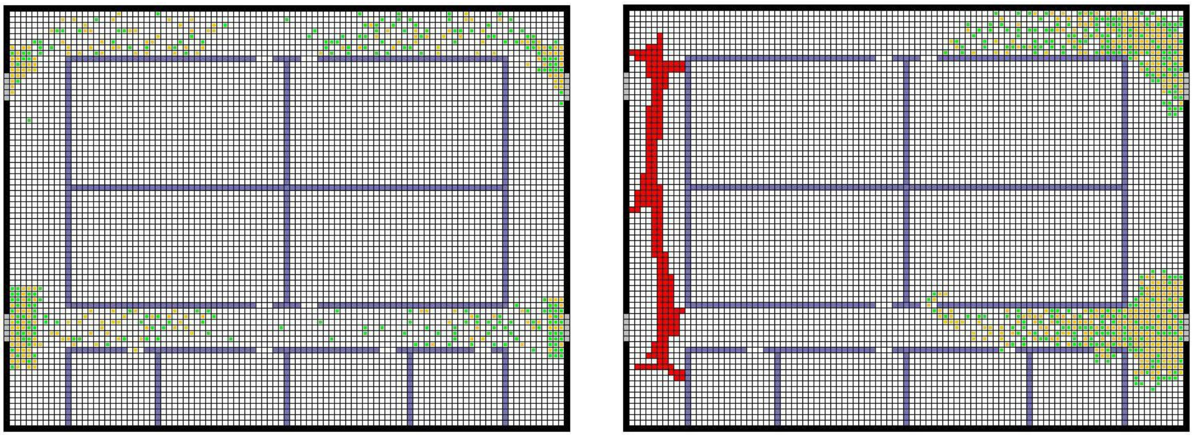

Fig. 6. (left) Case E. Without fire, (right) Case F. With fire (in red). 50% A_{NE}, 50% E_1 for both cases. Approximately at half of the evacuation process

Table 3 shows for each case of study, the number of agents of every type that evacuated for each exit. Comparing cases A vs. B, C vs. D and E vs. F, we can see how the agents in the presence of the fire they decide to go to the exits further away from the danger.

5. Conclusions

We have presented a model to perform simulation studies of evacuations aimed at observing people in emergency situations. The proposed model consists of two sub-models, called Environmental Model (EsM) and Pedestrian Model (PsM). The EsM, based on CA, manages the spatial configuration of the environment and models the processes of diffusion of smoke and fire. In this paper, we extend the pedestrian model and propose a behaviour-based agents approach that has the particularity of each behaviour is defined as high-level actions that a person can take as a strategy to follow during an evacuation. Furthermore, extending this concept and considering that for a dynamic evacuation, people can change their strategy originally chosen, now the agent will be equipped with a deterministic finite automaton to reflect these changes of strategies. The implementation of both, the high-level primitive behaviours along with the behaviours engine, is able to model in a representative way the observed phenomena in real evacuations. The current engine is composed of four high-level behaviours, which are conceived as more than simple atomic actions that the agent can perform.

This resultant hybrid model along with the computational methodology allows us build an artificial environment populated with autonomous agents and to experiment with different configurations of agents which are capable of interacting with each other.

The paper develops a series of experiments. First, we ran experiments with agents not familiar with the environment and therefore they had to follow the signs to make the evacuation process.These experiments intended to show some of the problems that can arise when a public environment has not been carefully signalled. In the second series of experiments we used the same environment for all cases, but with and without fire; varying configurations of the individuals placed in it. The goal was to know the impact of performing an evacuation where some of the exits are blocked by fire along the evolution of the model.

It was observed that in certain situations, the emergent behaviour that arises from the interaction between the agents generates a certain degree of disorganisation in the evacuation, which causes an increase in the evacuation times.

The experiments not only checked the impact of individual behaviour in the time of evacuation, but also analysed some of the events that act as trigger for a change of behaviour in the agent. Among others, it was examined the impact of distance, population density and width of the exits.

One of the main advantages of the proposed model with respect to current CA models, is that we can describe a set of individuals with heterogeneous behaviours and provide a framework that will allow us to enhance and add new behaviours to the existing ones, as we plan as future work.

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