Biomimicry of Crowd Evacuation with a Slime Mould Cellular Automaton Model

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Abstract. Evacuation is an imminent movement of people away from sources of danger. Evacuation in highly structured environments, e.g. building, requires advance planning and large-scale control. Finding a shortest path towards exit is a key for the prompt successful evacuation. Slime mould *Physarum polycephalum* is proven to be an efficient path solver: the living slime mould calculates optimal paths towards sources of attractants yet maximizes distances from repellents. The search strategy implemented by the slime mould is straightforward yet efficient. The slime mould develops may active traveling zones, or pseudopodia, which propagates along different, alternative, routes the pseudopodia close to the target loci became dominating and the pseudopodia propagating along less optimal routes decease. We adopt the slime mould's strategy in a Cellular-Automaton (CA) model of a crowd evacuation. CA are massive-parallel computation tool capable for mimicking the Physarum's behaviour. The model accounts for Physarum foraging process, the food diffusion, the organism's growth, the creation of tubes for each organism, the selection of optimum path for each human and imitation movement of all humans at each time step towards near exit. To test the efficiency and robustness of the proposed CA model, several simulation scenarios were proposed proving that the model succeeds to reproduce sufficiently the Physarum's inspiring behaviour.

1 Introduction

The need for realistic and efficient in case of emergency crowd dynamics modeling approaches has been considered a scientific topic of great importance. Having in

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mind that our safety and comfort depend crucially on our fellow crowd members and on the design and operation of the facility we are in, the quest of proper computational tools for modeling crowd behaviour is continuous.In the past, the main constraint in deep studying of crowd behaviour was the large number of required computations and the respective limitation of computational resources. Crowd was modeled as homogeneous mass characterised by properties of a moving fluid. In specific, pedestrian movement simulation models can mainly be categorized into macroscopic and microscopic ones. Macroscopic models focus on the total number of the members of the crowd. In other words, they study the major characteristics of the flow of the individuals rather than the features of the individuals themselves. Microscopic models study the attitude of each of the individuals and their interaction with the other members of the crowd. Furthermore, microscopic models describe the spatial and temporal behavior of each individual. The response of such models is very interesting, since they manage to represent virtual crowds to realistic autonomous behaviors. Cellular Automata (CA) [62] models, agent–based model and social–force models belong to this category [8, 11, 40, 18, 67, 49, 61].

While particle and CA based approaches mostly aim at generating quantitative results about pedestrian and crowd movement, agent based models sometimes aim at the generation of effective visualizations of believable pedestrian dynamics, and therefore the above approaches do not necessarily share the same notion of realism and validation [61]. Works like [8, 22] separate the pedestrians from the environment and grant them with a complex behavioral specification. Other approaches ([36, 45]) aim at generating visually effective and believable pedestrians and crowds in virtual worlds [45]. Finally, works like ([41]), employ cognitive agent models for different goals, but they are not generally focused on making predictions about pedestrian movement for sake of decision support. Social–force models describe the behavior of an individual through social sectors (virtual physical forces) that arise from the social attitude of the characters. Taking into consideration virtual social forces equivalent to real ones, such as repulsive interaction, friction forces and some fluctuations, they enable the resolution of Newton's motion equations of individuals. Compared to other models, social–force ones describe the attitude of an individual more realistically. Each motion parameter is assigned to physical meaning, it is unique for each of the members and its selection is often based on some empirical data. Social forces form the behavior of the members of the crowd through a combination of social–psychological and natural factors [20].

More specifically, Helbing *et al.* used repulsive and attractive forces to simulate the interaction among individuals and obstacles, offering a realistic behavior of individuals' prompting and variable percentages of flow as well. Furthermore, literature includes several studies and applications that use simulation approaches of particles for low–dense crowd formations. Specifically, Brogan and Hodgins [10] employed systems of particles and potentials in order to depict the motion of special–structured groups of people. Musse extended the model of social–forces, introducing the notion of individualism [9].

In CA based approach [62], the space under study is presented as a unified grid of cells with local attributes, which are generated by a set of rules that describe the behavior of the individuals [12]. The state of each cell is defined according to the rules, the state of the cell at the previous time step and the current state of neighboring cells. Recent approaches suggest that pedestrian crowd consists of discrete individuals, able to react with their surroundings. This requires a large number of computations. A possible solution could be modern computer power combined with the use of a CA computational model that is featured by massive parallelism. CA are very effective in simulating physical systems and solving scientific problems [49]. They can capture the essential features of systems where global behavior arises from the collective effect of simple components, which interact locally [15]. Furthermore, evacuation process is inherently complex, i.e. a system is multi–parameterized and its response cannot be easily estimated. There are interactions among occupants, places and environment and there are also socio–psychological parameters that should be taken under consideration [32, 66]. Evacuation could be defined as a non linear problem with many factors affecting it. Literature records many CA–based models investigating crowd behavior under various circumstances. The impact of environmental conditions [14, 42, 59, 67] and bi–directional pedestrian behavior [63, 25] has been examined. Interactions among pedestrians, friction effects [31, 43]. and herding behavior [40, 18] have also been considered. Furthermore, CA originated models are reported that focus on human behaviors, such as inertial effects, unadventurous effect and group effect [68]. Some models treat pedestrians as particles subject to long–range forces [7] and others use walkers leaving a trace by modifying the underground on their paths [11].

Macroscopic models focus on specific attitudinal attributes of separate members as well as on a generic handling of the pedestrians as a flow of individuals. Such models are very important in evaluating and predicting the needs of vehicle traffic or studying the dynamics of large scale constructions. In this category belong the models of regression that make use of statistically established relations on flow variables, in order to predict flow procedures of individuals under certain circumstances [35]. The models of route choice describe the path searching based on the concept of practicality. The members choose their destination aiming at the maximizing of the benefits of their route (comfort, time of the trip, etc.) [23]. Anticipation models use Markov chain models to describe the way that crowd move from one node of the net to the other. The gas motion models use a proportion based on the fluid or gas dynamics as well as on partial differential equations, in order to describe how the density and the velocity of the crowd change with time [21].

Instead of using a single yet efficient model for simulation of the evacuation process, here the idea of mimicking the physarum behavior during its foraging process in order to get closer to food sources is analysed. In more details, the touchstone of our inspiration arrives from the fact that physarum as a real biological organism enables itself to find one of the best/shortest possible ways towards food in an almost complex yet well described process [2].

Thus, in [3] we shown in laboratory experiments and numerical simulation that if plasmodium (vegetative form) of Physarum is inoculated in a maze's peripheral channel and an oat flake (source of attractants) is placed in the maze's central chamber then the plasmodium grows toward the target oat flake and connects the flake with the site of original inoculation with a pronounced protoplasmic tube. The protoplasmic tube represents a path in the maze. The plasmodium solves maze in one pass because it is assisted by a gradient of chemo–attractants propagating from the target oat flake.

The driving force to do so arrives mainly from the need of self–preservation. Taking into account that in some cases and beyond quantum processes, the same need, i.e. self–preservation can be found typically in a macroscopic level to the humans similar to the physarum behaviour we are triggered to explore possible applications of the aforementioned phenomenological behaviour to advance our crowd evacuation models. Although such a so–called large scale phenomenon, i.e. human crowd evacuation is supposed to be hardly predictable, it tends to present some interesting features that worth further researching. Having in mind that the Physarum, beyond the simplicity of its plasmodium's body and the fact that it is extremely easy to cultivate and handle, has demonstrated complicated and robust computing capacity when it confronted solving mazes problems [37]. Due to this capacity it can be considered as a fine candidate for modelling in an unconventional way the crowd evacuation process. Nevertheless, real time experiments with Physarum are time consuming; thus, is apparent the necessity of modelling its behaviour and the emergent computation abilities. Towards this direction, some slime mould models have been already proposed granting optimistic results. In specific, Tero and Nakagaki [54] introduced a mathematical model for mimicking of the true slime mold adaptive dynamics while constructing tubular networks. A multi–agent model was proposed by Jones *et al.* [26], while some Cellular Automata (CA) based models were proposed by Gunji *et al.*, who showed that their latticeagents–based model, namely CELL, is moving like an amoeba [19], as well as by Liu *et al.* who introduced an enhanced version of the agents–based CELL [33], by Tsompanas and Sirakoulis, who presented a CA model to simulate the plasmodiums foraging strategy and formation of a tubular network [57] and more recently by Kalogeiton *et al.* proposing a CA model for slime mould sufficient enough to result in successful Simultaneous Localisation and Mapping (SLAM) for robotic applications [27].

In this chapter by bio–mimicking Physarum's behaviour, a CA based crowd evacuation model is described in detail. In particular, the proposed CA model takes into account while mimicking the Physarum foraging process, the food diffusion, the organism's diffusion, the creation of tubes for each organism, the selection of optimum tube for each human in correspondence to the under study crowd evacuation and finally the movement of all humans at each time step towards near exit. All these procedures are repeated during the evolution of the CA model, as many times needed until all humans exit the under study indoor environment. It should be mentioned that in the proposed model all the characteristics of the space as well as of the humans' movement are considered based on the related pedestrian dynamics literature. To test the efficiency and the robustness of the presented CA model several simulation scenarios were proposed. More specifically, five different experimental results that indicate and prove the integrity of the algorithm were introduced. In all the examined cases the efficiency of the proposed evacuation model was sufficiently indicated in qualitative manner by the existence of basic crowd characteristics, such as clustering effects, the buildup of pressure, congestion at the exits, clogging effects at bottlenecks, jamming at widening and arching effects, which became apparent in most of the under study environments. All these results confirm the effectiveness of the proposed model for human evacuation scenarios.

The paper is structured as follows. In Section 2 some preliminaries on the *P. polycephalum* organism and CA basic theory are presented. Moreover, the preliminaries and the basic assumptions of the proposed here CA crowd evacuation model are given in Section 3, while the same Section 3 outlines the proposed here model in detail enlighten all the metaphors and simplifications needed to transform the Physarum foraging process to a efficient CA based crowd evacuation model. The results of the aforementioned model applied in fivedifferent simulation environments are depicted in Section 4. Finally, conclusions are drawn in Section 5.

2 Preliminaries: Physarum and CA Theory

2.1 Physarum

Plasmodium is a vegetative stage of the acellular slime mould *P. polycephalum*, a syncytium, that is, a single cell with many nuclei, which feeds on microscopic particles [53]. When foraging for its food the plasmodium propagates towards sources of food particles, surrounds them, secretes enzymes and digests the food. Typically, the plasmodium forms a congregation of protoplasm covering the food source. When several sources of nutrients are scattered in the plasmodium's range, the plasmodium forms a network of protoplasmic tubes connecting the masses of protoplasm at the food sources.

The plasmodium is a unique user–friendly biological substrate from which experimental prototypes of massive–parallel amorphous biological computers are designed [2]. During its foraging behaviour the plasmodium spans scattered sources of nutrients with a network of protoplasmic tubes. The protoplasmic network is optimised to cover all sources of food and to provide a robust and speedy transportation of nutrients and metabolites in the plasmodium body. The plasmodium's foraging behaviour can be interpreted as computation. Data are represented by spatial configurations of attractants and repellents, and results of computation by structures of a protoplasmic network formed by the plasmodium on the data sets [39, 38, 2]. The problems solved by plasmodium of *P. polycephalum* include shortest path [39, 38], implementation of storage modification machines [1], Voronoi diagram [46], Delaunay triangulation [2], logical computing [58], and process algebra [44]; see overview in [2].

In [4] we conducted pioneer laboratory experiments with Nylon terrains of USA and Germany. We used the Physarum to approximate route 20, the longest road in USA, and autobahn 7, the longest national motorway in Europe. We found that Physarum builds longer transport routes on 3D terrains, comparing to flat substrates yet sufficiently approximates man–made transport routes studied. We demonstrate that nutrients placed in destination sites affect performance of Physarum, show how the Physarum navigates around elevations. In cellular automaton models of the Physarum we shown variability of the protoplasmic routes might depends on physiological states of the slime mould. Results presented will contribute towards development of novel algorithms for sensorial fusion, information processing, and decision making, and will provide inspirations in design of bio–inspired amorphous robotic devices.

Our results [4] demonstrated that Physarum is capable of solving practical tasks of path–finding even when confined to a non–friendly substrate of bare plastic. Thus we decided to test the Physarum's abilities on imitating tasks of evacuation in a physical model of a building.

2.2 CA Theory

Cellular automata (CA) are models of physical systems, where space and time are discrete and interactions are local [13]. In brief, CA were originally proposed by John von Neumann (1966), as formal models of self–reproducing organisms, who was thinking of imitating the behaviour of a human brain in order to build a machine able to solve very complex problems [62]. His ambitious project was to show that complex phenomena can, in principle, be reduced to the dynamics of many identical, very simple primitives, capable of interacting and maintaining their identity [13]. Following a suggestion by Ulam [1952], von Neumann adopted a fully discrete approach, in which space, time and even the dynamical variables were defined to be discrete. Consequently, CA are very effective in simulating physical systems and solving scientific problems, because they can capture the essential features of systems where global behaviour arises from the collective effect of simple components which interact locally [65].

A CA consists of a regular uniform n-dimensional lattice (or array), usually of infinite extent. At each site of the lattice (cell), a physical quantity takes on values. The value of this physical quantity over all the cells is the global state of the CA, whereas the value of this quantity at each site is its local state. Each cell is restricted to local neighborhood interaction only and, as a result, it is incapable of immediate global communication [62].

A CA is characterized by five properties:

1. The number of spatial dimensions (n).
2. The width of each side of the array (w). w_j is the width of the j^{th} side of the array, where $j = 1,2,3,...,n$.
3. The width of the neighborhood of the cell (r).
4. The states of the CA cells.
5. The CA rule, which is an arbitrary function F.

The state of a cell, at time step $(t+1)$, is computed according to F, a function of the state of this cell at time step (t) and the states of the cells in its neighborhood at time step (t). The neighborhood of each cell is defined by variable N. For a 2-d CA, two neighborhoods are often considered: Von Neumann and Moore neighborhoor, respectively. Equation 1 defines the Von Neumann neighborhood of range r.

$$N^N_{(x_0,y_0)} = \{(x,y) : |x-x_0| + |y-y_0| \leq (r)\}. \quad (1)$$

For a given cell (x_0, y_0) and range r, Moore neighborhood can be defined by the following formula:

$$N^M_{(x_0,y_0)} = \{(x,y) : |x-x_0| \leq (r), |y-y_0| \leq (r)\}. \quad (2)$$

In most practical applications, when simulating a CA rule, it is impossible to deal with an infinite lattice. The system must be finite and have boundaries. Clearly, a site belonging to the lattice boundary does not have the same neighborhood as other internal sites. In order to define the behavior of these sites, neighborhood is extending for the sites at the boundary, thus leading to various types of boundary conditions such as periodic (or cyclic), fixed, adiabatic or reflection.

CA have sufficient expressive dynamics to represent phenomena of arbitrary complexity [65, 16, 29, 50] and at the same time can be simulated exactly by digital computers, because of their intrinsic discreteness, i.e. the topology of the simulated object is reproduced in the simulating device [60]. The CA approach is consistent with the modern notion of unified space-time. In computer science, space corresponds to memory and time to processing unit. In CA, memory (CA cell state) and processing unit (CA local rule) are inseparably related to a CA cell [51, 48]. Furthermore, they can easily handle complicated boundary and initial conditions, inhomogeneities and anisotropies [51]. In addition, algorithms based on CA run quickly on digital computers [56]. Models based on CA lead to algorithms, which are fast when implemented on serial computers, because they exploit the inherent parallelism of the CA structure. These algorithms are also appropriate for implementation on massively parallel computers [52], such as the Cellular Automaton Machine (CAM) [64] or Field Programmable Gate Arrays (FPGAs) [17, 34, 24].

3 Proposed Bio–inspired Evacuation Method

As mentioned before, the method that is proposed in this paper refers to the design and implementation of a novel bio–inspired/bio–mimicking model for human evacuation scenarios. This method is based on the plasmodium of *P. polycephalum* coupled with the CA parallel computational tool.

In particular, it is attempted to simulate the movement of a crowd, when the crowd is located in an indoor environment and is trying to evacuate it. Each human located in the environment is represented by plasmodium of Physarum, acquiring the functionalities the organism has under specific circumstances. This particular microorganism is deployed into a nutrient–poor substrate, which represents the indoor to–be–evacuated environment. The position of each organism is the corresponding position of each individual human, while at the same time all exits of the environment are considered as food sources for the Physarum. In that way, all plasmodiums are spreading towards food source and eventually construct a tubular network, the cytoplasm, which connects optimally each plasmodium with the food sources, i.e. each human with the exits of the space. Therefore, for each human the optimum and shortest path/ tube is selected and is the one that the human follows in order to exit the environment. In case the path, which a human follows, is interrupted, meaning that the human is not able to move since the target position is occupied by another human, the plasmodium is required to re–diffuse and hence, to re–create a network based on the new conditions. This procedure results in the successful evacuation of indoor environments.

3.1 Space Delineation

All evacuation scenarios examined in this paper refer to indoor environments. Thus, it is important to determine the space in which the evacuation takes place.

According to CA the space examined in each case is divided to cells, thus resulting in a CA grid. Each cell is individual and independent not to mention the fact that it is considered as possible position (for humans, obstacles, exits etc.). The dimension of each cell is crucial, since it should be large enough to represent a human and small enough compared to the total space. According to recent studies demonstrated in [11], each human can cover a minimum area of: 40×40 cm^2. This dimension has been chosen, since according to the corresponding studies the proposed area represents the region a human needs when standing in order to feel comfortable with the environment and at the same time in order not to be possible for another human to occupy the same space. The basic definitions that refer to the under study space are summed up as follows:

- Assume that the space Ω is rectangular, without loss of generality, with dimensions: $L_1 \times L_2$ m^2.
- The space Ω is partitioned into computational cells $c_{i,j}$, where $c_{i,j} = 1,\ldots,K$, such that $c_{i,j} \cap c_{m,n} = \oslash, (i,j) \neq (m,n)$ and $\bigcup_{i,j=1}^{K} c_{i,j} = \Omega$.
- The number of cells $c_{i,j}$ of each side of the under study space is $N_{1c_{i,j}} = \frac{L_1}{0.4}$ and $N_{2c_{i,j}} = \frac{L_2}{0.4}$, respectively.
- Thus, it holds that: $i = 1,\ldots,N_{1c_{i,j}}$ and $j = 1,\ldots,N_{2c_{i,j}}$.
- Define the total number of cells as: $N_{c_{i,j}} = N_{1c_{i,j}} \times N_{2c_{i,j}}$.

3.2 Initial Declarations

As mentioned before, the main goal of this method is the simulation of the human evacuation process. To begin with, it is important to define the matching rules between the real environment and its corresponding biological one. The elements needed in order to design an evacuation model could be summed up as the position of each human inside the space, the position of the exits and of the obstacles into the environment and of course, the remaining ”free space”, meaning the space that is not occupied neither by humans nor by obstacles/exits.

Thus, the matching of each of these elements with their corresponding biological ones derives from the human ”representation”. Each human is represented by the Physarum, and it is assumed that an initial quantity of the organism in plasmodium state is placed - and hence accumulated - in the particular cell that is occupied by the corresponding human. As a result, each human is represented by a plasmodium while in the rest of the space (including both the free space and the obstacles) no organism exists. As far as the exits of the environments is concerned, these are represented by the food sources, meaning that for each cell an exit exists, a food source is placed.

At this point, it should be mentioned the environment circumstances under which the Physarum will function. According to [47] in case the plasmodia of Physarum develop in a nutrient–rich substrate (agar gel containing crushed oat flakes) the colliding protoplasmic fronts merge. On the other hand, when the plasmodia develop on a nutrient-free substrate, protoplasmic tubes are formed between the loci of the concentrated cytoplasm and the food sources. Figure 1, which follows, illustrates the development of plasmodia on a plain substrate during time, proving the formation of the tubular network between the food sources. This image is based on real biological experiments [47].

The formation of the tubular network constitutes the main reason for having chosen this microorganism to represent the human. In an evacuation scenario each human follows a path to reach a building exit. The ability of the Physarum to find a shortest path creating the tubes is the most profound feature exploited by this method. That means that the organism is able to find the shortest path between its position and the exit carving in that way the route that the human will follow. It should be noted that, the environment that each cytoplasm is developed, is considered to be nutrient–free.

In this nutrient–free substrate the microorganism can be developed only under appropriate circumstances. Hence, the coordinates of the inaccessible by humans regions of the real environment (e.g. the obstacles, the walls etc.) indicate to the corresponding coordinates of the assumed substrate, in which physical barriers meet. The term physical barrier refers mainly to constrained circumstances under which the plasmodium is not able to develop, such as under light regime [55] or next to grains of salt [5].Thus, the representation of obstacles and walls could be done by using light. Figure 2 demonstrates an example of how Physarum's plasmodium responds to light.

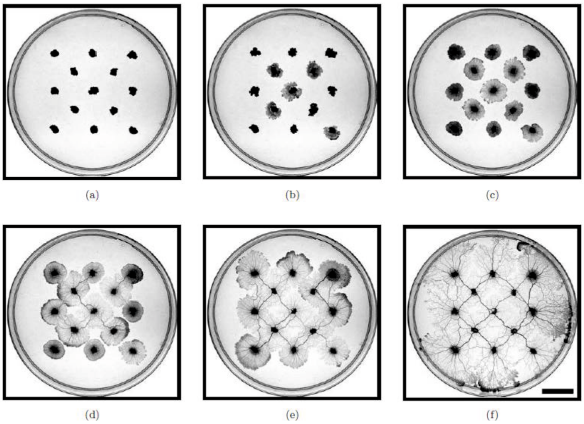

Fig. 1 Development of plasmodia on a nutrient-free substrate. The Physarum is concentrated in different locations in the substrate - shown by black color in (a) - and then the network is formulated. Each figure indicates the state of the plasmodia (a) 12 h, (b) 23 h, (c) 34 h, (d) 47 h, (e) 69 h, (f) 80 h after the inoculation on the substrate. (d) and (e) When the plasmodia come to contact, they show avoidance of the other plasmodia, though they fuse at some points, in a very limited manner. (f) Tube formation proceeded with time, and the enhanced tubular network is constructed. (Scale Bar 2 cm) [47]

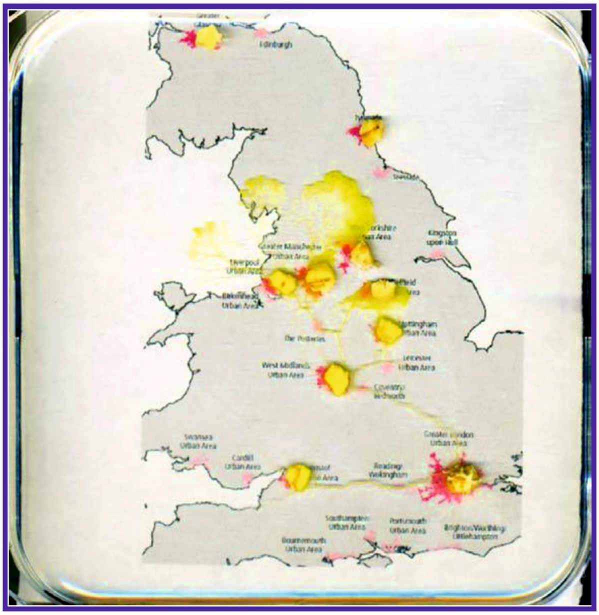

Fig. 2 The developing Physarum network adopted by [5]. Typical experimental setup of UK transportation network where ten most populous urban areas are represented by oat flakes, plasmodium is inoculated in London, the plasmodium spans oat flakes by protoplasmic transport network.

3.3 Method Overview

After the determination of the basic contents of the method, a detailed description of the proposed bio–inspired evacuation algorithm follows. The initial steps are the food diffusion and the organism growth. The diffusion of the food as well of the microorganism takes place based on the proposed here CA model.

Chemo–attractant Diffusion from Sources of Nutrients. After defining earlier the space Ω and the number $N_{c_{i,j}}$ of cells $c_{i,j}$, assume that:

- In the $N_{c_{i,j}}$ cells there are K active cells, such that $K \subseteq N_{c_{i,j}}$.
- The set of active cells is defined as $A = \left\{c_{i,j}^{A_1}, c_{i,j}^{A_2}, c_{i,j}^{A_3}, \ldots, c_{i,j}^{A_K}\right\}$.
- The state of these K active cells is denoted by $p_{i,j}$.

Active cells are the cells that the plasmodium is able to diffuse and therefore to grow cytoplasm. These cells correspond to the so called free space of the environment.

- The set of repellents $R = \{R_1, R_2, R_3, \ldots\}$ is defined as the total of cells that the plasmodium cannot reach.
- Let r be the number of repellents R, so that: $R = \{R_1, R_2, R_3, \ldots, R_r\}$.
- Define $\left\{c_{i,j}^{R_1}, c_{i,j}^{R_2}, c_{i,j}^{R_3}, \ldots, c_{i,j}^{R_r}\right\}$ the corresponding cells of the set of repellents $R = \{R_1, R_2, R_3, \ldots, R_r\}$.

Repellents are are physical stimuli that cause an organism to migrate away or react adversely. It is known that the plasmodium of Physarum avoids light and salt. Thus, domains of high illumination together with salt concentrations are repellents such that each repellent R is characterised by its position and intensity of illumination or force of repelling.

- The set of attractants $F = \{F_1, F_2, F_3, \ldots\}$ are sources of nutrients on which the plasmodium feeds.
- Let s be the number of food sources F, so $F = \{F_1, F_2, F_3, \ldots, F_s\}$.
- Let $\left\{c_{i,j}^{F_1}, c_{i,j}^{F_2}, c_{i,j}^{F_3}, \ldots, c_{i,j}^{F_r}\right\}$ be the corresponding cells of the set of food sources $F = \{F_1, F_2, F_3, \ldots, F_s\}$.

It is still the subject of discussion on how exactly plasmodium feels the presence of attracts. Indeed diffusion of some kind is involved [6]. Thus, the representation of the diffusion process both of the food and the plasmodium takes place based on the proposed here CA model. The neighbourhood chosen for both cases is the Moore neighbourhood, since according to [28, 30] is appropriate and capable of simulating the diffusion of a liquid and of a smell.

The food diffusion takes place only to the K active cells, given that the smell can pass through a human, which occupies a cell, but not through a wall. The smell, $Smell_{i,j}$, starts from the cells $\{c_{i,j}^{F_1}, c_{i,j}^{F_2}, c_{i,j}^{F_3}, \ldots\}$, that represent the exits, namely the food sources, and spreads at each time step t to their neighbour cells according to Equation 3:

$$Smell^{t+1}_{(i,j)} = Smell^{t}_{(i,j)} + s_1 \times (SVN) + s_2 \times (RMN), \tag{3}$$

where SVN expresses the *von Neumann* neighbourhood and it is defined as follows:

$$\begin{aligned} SVN = Smell^{t}_{(i-1,j)} + Smell^{t}_{(i,j-1)} + Smell^{t}_{(i,j+1)} + \\ + Smell^{t}_{(i+1,j)} - 4 \times s_4 \times Smell^{t}_{(i,j)} \end{aligned} \tag{4}$$

and RMN expresses the remaining cells for the *Moore* neighbourhood to be created and is defined as:

$$\begin{aligned} RMN = Smell^{t}_{(i-1,j-1)} + Smell^{t}_{(i-1,j+1)} + Smell^{t}_{(i+1,j-1)} + \\ + Smell^{t}_{(i+1,j+1)} - 4 \times s_4 \times Smell^{t}_{(i,j)}, \end{aligned} \tag{5}$$

where: $s_2 = s_1 \times s_3$. The higher the values of parameters s_1, s_2, s_3 are, the quicker the diffusion of the food smell is. Parameter s_4 indicates the power of attraction of the Physarum by the food smell. The values of the $Smell^{t}_{(i,j)}$ variable range from 0 to N_{vs}, where $N_{vs} \in N$ is a determine integer number. In a cell $c_{i,j}$, the greater the value N_{vs} is, the more food smell exists in this particular cell.

Figure 3a illustrates a space, more precisely a corridor. The black color represents the walls, the blue the exits and the yellow face the human. In Figure 3 the food diffusion of this space is demonstrated. The white color represents the food source, while the more shaded a cell is, the less food smell exists in that cell ($N_{ns} \rightarrow 0$). All colors expect the red one represent the active cells K. Red color represents the walls of the environment, where no food smell has diffused.

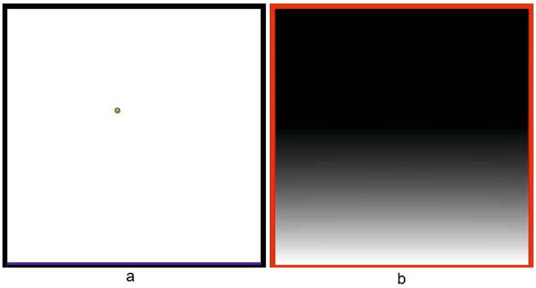

Fig. 3 Space before and after food diffusion: a) A corridor –white color– with a human –yellow face– with multiple exits which are represented with blue color. b) Food diffusion: The white color represents the food sources, whereas the more the color verges the black, the less the food smell has spread. Red color represents the walls, where no food smell has diffused

Organism's Growth. After the food diffusion, the growth of the microorganism takes place. It is important for the smell of the food sources to be spread primarily, since the growth of each plasmodium depends on the food diffusion. That means that each cytoplasm is directed to the closest food source in order to be fed. Thus, the microorganism should be able to detect the direction the food comes from and given that the *P.* has only the ability to detect the smell of the food, the food smell should have been diffused.

Once more, the diffusion is carried out only in the active cells:

$$A = \left\{ c_{i,j}^{A_1}, c_{i,j}^{A_2}, c_{i,j}^{A_3}, \ldots, c_{i,j}^{A_K} \right\},$$

meaning that each microorganism can spread at whichever cell is not occupied by an obstacle or a wall. However, the organism can be propagated in a cell that is occupied by another organism, namely by another human. This happens, since the organisms during the diffusion process are independent from each other and they are considered as separate organisms, not able to merge. This could be feasible, considering as many nutrient-free substrates as they number of humans/ microorganisms.

- Let $H = \{H_1, H_2, , H_3, \ldots\}$ be the humans of the space Ω.
- Let N_H be the number of H and therefore of the organism's, so that: $H = \{H_1, H_2, H_3, \ldots, H_{N_H}\}$.
- Let $\left\{ c_{i,j}^{H_1}, c_{i,j}^{H_2}, c_{i,j}^{H_3}, \ldots, c_{i,j}^{H_{N_H}} \right\}$ be the cells, where the humans H are located.
- Define $ConOrg_{(i,j)}$ as the concentration of the plasmodium of Physarum at each position $\left\{ c_{i,j}^{H_1}, c_{i,j}^{H_2}, c_{i,j}^{H_3}, \ldots, c_{i,j}^{H_{N_H}} \right\}$ that the H human is located.

The growth of the micro–organism starts from the corresponding position $c_{i,j}^{H_\tau}$ of the human $H_\tau, \tau \in [1, \ldots, N_H]$ and continues/ proceeds for all cells of the environment according to:

$$ConOrg_{(i,j)}^{t+1} = ConOrg_{(i,j)}^{t} + c_1 \times MVN + c_2 \times LMN, \tag{6}$$

where MVN expresses the *von Neumann* neighbourhood and it is defined as follows:

$$\begin{aligned} MVN = \left(1 + DF_{(i-1,j)}^{t}\right) \times ConOrg_{(i-1,j)}^{t} + \left(1 + DF_{(i,j-1)}^{t}\right) \times ConOrg_{(i,j-1)}^{t} + \\ + \left(1 + DF_{(i,j+1)}^{t}\right) \times ConOrg_{(i,j+1)}^{t} + \left(1 + DF_{(i+1,j)}^{t}\right) \times ConOrg_{(i+1,j)}^{t} - \\ -4 \times c_4 \times ConOrg_{(i,j)}^{t} \end{aligned} \tag{7}$$

and LMV expresses the cells left for the *Moore* neighbourhood to be completed and is defined as follows:

$$\begin{aligned} LMV = \left(1 + DF_{(i-1,j-1)}^{t}\right) \times ConOrg_{(i-1,j-1)}^{t} + \left(1 + DF_{(i-1,j+1)}^{t}\right) \times ConOrg_{(i-1,j+1)}^{t} + \\ + \left(1 + DF_{(i+1,j-1)}^{t}\right) \times ConOrg_{(i+1,j-1)}^{t} + \left(1 + DF_{(i+1,j+1)}^{t}\right) \times ConOrg_{(i+1,j+1)}^{t} - \\ -4 \times c_4 \times ConOrg_{(i,j)}^{t}, \end{aligned} \tag{8}$$

where $DF_{(i,j)}^{t}, \forall (i,j) \in F \subseteq \Omega$ denotes the direction of the food smell $Smell_{(i,j)}^{t}$ that the organism H_τ detects for each cell at each time step t. The higher the values of parameters c_1, c_2, c_3 are, the quicker the growth of the organism's mass, respectively, is. The c_4 parameter indicates the power of attraction of the Physarum by the food smell.

If there is no food smell then

$$DF^t_{(i,j)} = 0, \forall i,j \in [-1,1] : i \; or \; j \neq 0 \tag{9}$$

and if the food smell comes from the direction: (k,l), where $k,l \in [-1,1]$ then

$$DF^t_{(i+k,j+l)} = c_5 \; and \; DF^t_{(i-k,j-l)} = -c_5, \forall i,j \in [-1,1] : i \; or \; j \neq 0 \tag{10}$$

so that:

$$\sum_{\substack{i,j=-1 \\ i||j\neq 0}}^{1} DF^t_{i,j} = 0, \tag{11}$$

where it holds that: $c_2 = c_1 \times c_3$ and the variable c_5 indicates the influence the food smell $Smell^t_{(i,j)}$ has to the organism's growth $ConOrg^t_{(i,j)}$. The values of $ConOrg^t_{(i,j)}$ range from 0 to N_{vo}, where N_{vo} is a determine integer number. In a cell $c_{i,j}$, the greater the value N_{vo} is, the more mass of the organisms propagated in this particular cell.

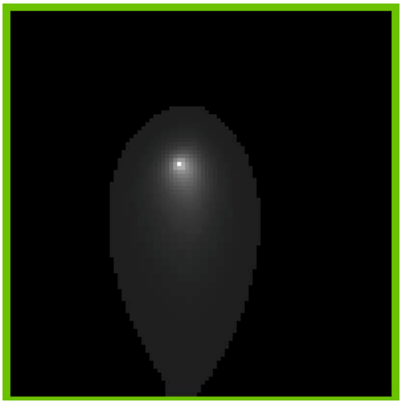

Fig. 4 The growth of the plasmodium *Physarum polycephalum*: The green color represents the walls, where no organism has been grown, whereas in the rest of the space, the more shadowed the color is, the less organism has propagated in that cell

Figure 4 illustrates the growth of the Physarum in the environment presented in Figure 3a. The white color represents the accumulated mass of the organism in its initial position (human's position), while the more shaded a cell is, the less the plasmodia have been grown in that cell ($N_{vo} \rightarrow 0$). All colors expect the green one represent the active cells A. Green color represents the walls of the environment, where there is no possibility for the organism to spread.

Protoplasmic Tubes' Creation. After the growth process, the creation of protoplasmic tubes follows:

- Let $C = \{C_1, C_2, C_3, \ldots\}$ be the set of the total protoplasmic tubes formed by all organisms.
- Let N_C denote the total number of tubes C. Hence the set C is defined as: $C = C_1, C_2, C_3, \ldots, C_{N_C}$
- Let $T_H \subseteq C$ denote the total tubes of the human H. $T_H = C_1, C_2, C_3, \ldots$.

Consider the Physarum/human $H_\tau, \tau \in [1, \ldots, N_H]$ located in the cell $C_{i,j}^{H_\tau}$ and the exitfood source $F_\lambda, \lambda \in [1, \ldots, s]$. It holds that:

$$\forall F_\lambda, H_\tau, \lambda \in [1, \ldots, s], \tau \in [1, \ldots, N_H] \exists_{=1} C_\lambda^{H_\tau}, \tag{12}$$

where $C_\lambda^{H_\tau}$ denotes the tube of the human H_τ with the exit F_λ.

- Let $T_H \subseteq C$ denote the total tubes of the human H. It holds that:

$$T_H = \left\{C_{F_1}^H, C_{F_2}^H, \ldots, C_{F_s}^H\right\}, \text{ where } s \rightarrow N_{umber} \text{ of } F. \tag{13}$$

Therefore:

$$C = \bigcap_{\tau=1}^{N_H} T_{H_\tau} = \left\{C_{F_1}^{H_1}, C_{F_2}^{H_1}, \ldots, C_{F_s}^{H_1}, C_{F_1}^{H_2}, C_{F_2}^{H_2}, \ldots, C_{F_s}^{H_2}, \ldots, C_{F_1}^{H_{N_H}}, C_{F_2}^{H_{N_H}}, \ldots, C_{F_s}^{H_{N_H}}\right\}, \tag{14}$$

where $\tau = 1, \ldots, N_H$ and $s \rightarrow N_{umber}$ of F,
therefore, the set C consists of all tubes created for all humans for all exits. Hence, the number N_C of elements of the set C is defined as:

$$N_C = s \times N_H. \tag{15}$$

That means that each organism –human– H creates as many tubes T as the number of exits s of the environment Ω.

Consider the Physarum/human $H_\tau, \tau \in [1, \ldots, N]$, located in the cell $C_{i,j}^{H_\tau}$ and the exit/food source $F_\lambda, \lambda \in [1, \ldots, s]$ located in the cell $C_{i,j}^{F_\lambda}$. The direction $D_{i,j}^t, \forall (i,j) \in A \subseteq \Omega$ of the food smell $Smell_{i,j}^t$ as described in Equations 8–11 resulted in the proper diffusion of the organism towards the exits F. The values, the diffusion $ConOrg_{i,j}$ of the H_τ organism –so called $ConOrg_{i,j}^{H_\tau}$ –(according to Equation 3) received, represent the concentration of the organism in each cell $c_{i,j}$.

Each tube $C_{F_\lambda}^{H_\tau}$, $\lambda \in [1, \ldots, s]$, $\tau \in [1, \ldots, N_H]$ consists of successional cells as follows:

$$C_{F_\lambda}^{H_\tau} = C_{i,j}^{H_\tau}, \ldots, C_{i,j}^{F_\lambda} \; \lambda \in [1, \ldots, s], \; \tau \in [1, \ldots, N_H]. \tag{16}$$

In particular, the construction of the protoplasmic tube $C_{F_\lambda}^{H_\tau}$ starts from the cell $C_{i,j}^{H_\tau}$, where the human H_τ and hence the main mass of the organism is located. Then, of all the adjacent cells of the initial cell $C_{i,j}^{H_\tau}$, it is chosen the cell $C_{i_{new},j_{new}}^{H_\tau}$ that:

$$ConOrg_{i_{new},j_{new}} = max\left\{ConOrg_{i+k,j+n}\right\} : c_{i+k,j+n} \notin C_{F_\lambda}^{H_\tau}, \quad (17)$$

where $k,n \in [-1,1] : k||n \neq 0$.

That means that from all adjacent cells, the cell chosen $C_{i_{new},j_{new}}^{H_\tau}$ is the one, in which the mass of the organism is the maximum as long as it does not already belong the tube cells, namely as long as the tube does not contain this cell. When this cell is chosen, the same process is followed in order for the tube $C_{F_\lambda}^{H_\tau}$ to be created. The construction ends to the F_λ food source, namely to the cell $C_{i,j}^{F_\lambda}$.

The same procedure is followed for the specific human H_τ for all the food sources\exits F_s. Thus, the set $T_{H_\tau} = \left\{C_{F_1}^{H_\tau}, C_{F_2}^{H_\tau}, \ldots, C_{F_s}^{H_\tau}\right\}$ with all the possible paths for the human to follow is created.

Figure 5 demonstrates the tubes created. Figure 5a illustrates a real experiment, where a microorganism is located in a nutrient–poor environment and creates a protoplasmic tube that connects its location\position with the food source located to the other side of the substrate. Figure 5b presents a space with one human and one exit. The human, which corresponds to the microorganism, is drawn with a yellow face, the walls and obstacles with black color and the tube with green.

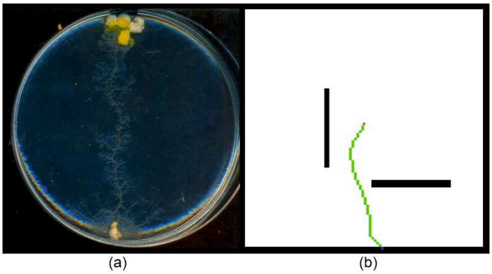

Fig. 5 Creation of tubes: a) An example of plasmodium attracted by source of nutrients [2]. Initially the plasmodium is placed in the southern part of disk and a group of intact oat flakes in the northern part. Plasmodium propagates towards the intact flakes and occupies them b) The plasmodium creates a tube with the exit demonstrated by green color

Figure 6 demonstrates the tubes created in cases where more than one human or more than one exits exist in the environment. Figure 6a illustrates a space with one human and two exits, while in Figure 6b there are two humans and two exits in the environment. In both cases the walls and the obstacles of the space are drawn with black color, the human with a yellow face and the tubes with green color. Consequently, it is quite obvious that each human, who imitates the functionality of the microorganism, is connected with protoplasmic tubes with every exit of the space.

However, only one tube is able to indicate the path the human will follow, given that a human follows one route. Hence, the most appropriate and representative of each humans motion tube should be selected.

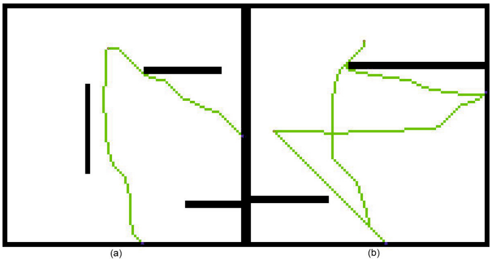

Fig. 6 Tube construction: a) A human in an environment with two exits. For each exit an individual tube is created b) Two humans with the corresponding tubes towards the exits

Selection of Shortest Tube. As it is made clear, the number of elements of each tube $C_{F_\lambda}^{H_\tau}, \forall \lambda \in [1, \ldots, s]$, $\forall \tau \in [1, \ldots, N_H]$ of the set $T_{H_\tau} = C_{F_1}^{H_\tau}, C_{F_2}^{H_\tau}, \ldots, C_{F_s}^{H_\tau}$ for a human H_τ is not a static number, but it depends on the number of cells $C_{i,j}$ the tube $C_{F_\lambda}^{H_\tau}$ consists of.

- Let assume $NCel_{C_{F_\lambda}^{H_\tau}}^{H_\tau}$ denote the number of cells of each tube for each human H_τ. It holds that:

$$1 \leq NCel_{C_{F_\lambda}^{H_\tau}}^{H_\tau} \leq K \subset N_{C_{i,j}}. \tag{18}$$

Thus, for the chosen tube $C_{F_\lambda ch}^{H_\tau}$ of a human H_τ it holds that:

$$NCel_{C_{F_\lambda}^{H_\tau}}^{H_\tau} = min\left\{NCel_{C_{F_1}^{H_\tau}}^{H_\tau}, NCel_{C_{F_2}^{H_\tau}}^{H_\tau}, \ldots, NCel_{C_{F_s}^{H_\tau}}^{H_\tau}\right\}, \tag{19}$$

which can be explained as follows: The chosen tube $C_{F_\lambda ch}^{H_\tau}$ for a human H_τ is the one that contains the minimum number of elements $\left\{c_{i,j}^{H_\tau}, \ldots, c_{i,j}^{F_\lambda}\right\}$, i.e. the minimum number of cells, namely the tube that corresponds to the shortest path. In case two or more tubes consist of equal number of cells, then the one with the smallest Euclidean distance is chosen. Figure 7 demonstrates such an example. In an environment with two humans and two exits each human chooses as target exit the one that is located nearest to him.

Move towards Tube. The next step of the evacuation algorithm contains the human's movement along the path/tube created and selected earlier. The movement process depends on whether or not the position the human is about to go is occupied. Therefore, at each time step t each human checks whether or not she/he is able to move. If it is so, the human follows the path to the exit. If not, then the she/he has two options:

1. To remain motionless. This option connotes that the human waits until the position she/he wants to move into will be released.
2. To follow a new path that leads to the closest exit.

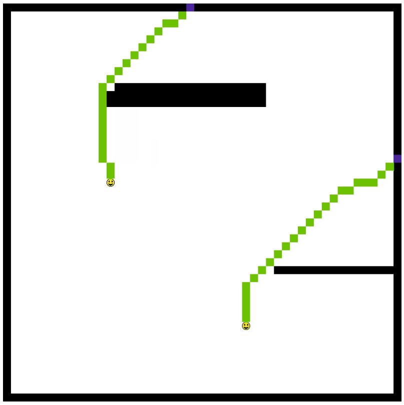

Fig. 7 An environment with two separate exits. From all tubes created for each human, only the one that connects him with the closest exit is chosen

To sum up, the proposed bio–inspired evacuation model is composed by: the food diffusion, the organism's growth, the creation of tubes for each organism, the selection of optimum tube for each human and finally by the movement of all humans at each time step. These steps are repeated as many times needed until all humans exit the environment.

4 Simulation Results for the Proposed Evacuation Model

As it is already known (Weidmann, 1993) the human velocity in areas with low people density approximately is set to be: $V_H = 1.34\ \mathrm{ms}^{-1}$. What is more, as already mentioned, each human occupies a single cell of the space that according to [11] corresponds to $0.4 \times 0.4\mathrm{m}^2$. Given that at one time step of the method each human is considered to be able to move by one cell, it can be concluded that each time step of the method approximately corresponds to 0.3 s –specifically to 0.298507 s in a real time experiment. The carried out simulation cases were enough and differentiate significantly so as to examine different well known test cases in corwd evacuation modeling. In specific five different representative examples are demonstrated, through which the whole evacuation procedure can be easily understood as well as the results of the evacuation scenarios can be visualized. In all five examples listed below, the values of the pre-mentioned parameters are set to be (see Table 1):

Table 1 General parameters of all evacuation scenarios regarding diffusion of the food as well as of the plasmodium of *Physarum*

Parameters of Food Diffusion	Values	Parameters of Organism's Diffusion	Values
s_1	0.1	c_1	0.1
s_3	0.01	c_3	0.01
$s_2 = s_1 \times s_3$	0.001	$c_2 = c_1 \times c_3$	0.001
s_4	1	c_4	1
–	–	c_5	0.3

4.1 Experiment 1

Initially, the environment to be evacuated was created. As first example a simple space is selected. The space is actually a corridor with multiple exits and without any obstacles. The parameters of this environment are shown in Table 2 below, while the images of the experiment are shown in Figure 8. As it can be easily observed all humans manage to exit the space successfully.

Table 2 The parameters of evacuation scenario No. 1

Parameters	Case 1
$L_1(width)$	$21.6m$
$L_2(height)$	$40m$
N_H	192
$s(exits)$	50
$N_{1C_{i,j}} = \frac{L_1}{0.4}$	54 cells
$N_{2C_{i,j}} = \frac{L_2}{0.4}$	100 cells
$N_{C_{i,j}} = N_{1C_{i,j}} \times N_{2C_{i,j}}$	54×100 cells
$Obstacles$	$None$
$t(Time\ Steps)$	88
$Real\ time$	$26.26s$

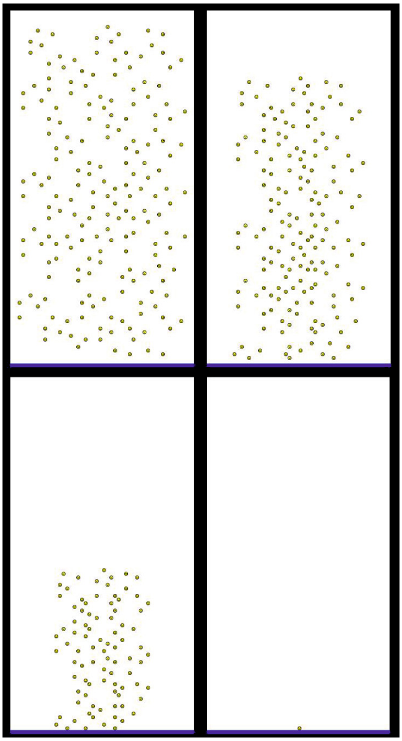

Fig. 8 Evacuation Scenario No. 1: A corridor with 50 exits, 192 humans and no obstacles

4.2 Experiment 2

In the second evacuation scenario a corridor is once more selected. However, this time the corridor consists of only one exit, meaning that at each time step only one human is able to exit the environment. The parameters of this environment are shown in Table 3 below, while the images of the experiment are shown in Figure 9. The main goal of this experiment is to point out the congestion in the exit. In such cases effects of building up pressure are observed (Helbing, Farkas, & Vicsek, Simulating Dynamical Features of Escape Panic, 2000), since humans are pressed to each other. What is more, in this case the prominent arching effects are observed as in real experiments.

4.3 Experiment 3

In this evacuation scenario an environment with two (2) exits is selected. These exits are not next to each other, they are placed on different sides of the under study

Table 3 The parameters of evacuation scenario No. 2

Parameters	Values
$L_1(width)$	$21.6m$
$L_2(height)$	$40m$
N_H	192
$s(exits)$	1
$N_{1C_{i,j}} = \frac{L_1}{0.4}$	54 cells
$N_{2C_{i,j}} = \frac{L_2}{0.4}$	100 cells
$N_{C_{i,j}} = N_{1C_{i,j}} \times N_{2C_{i,j}}$	54×100 cells
$Obstacles$	$None$
$t(Time\ Steps)$	192
$Real\ time$	$57.3s$

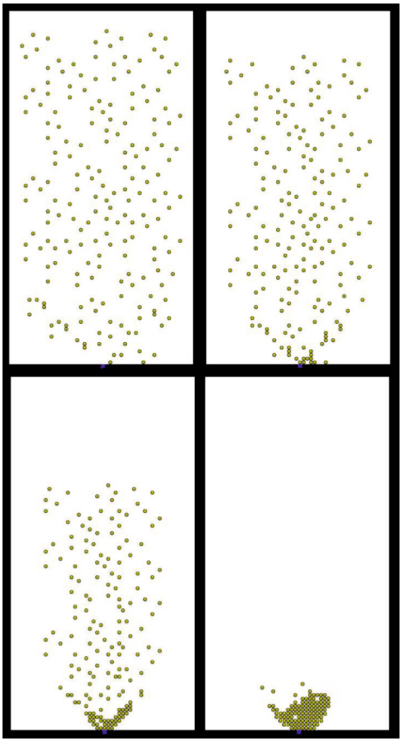

Fig. 9 Evacuation Scenario 2: A corridor with only one (1) exit, 192 humans and no obstacles

space in order to clarify the fact that each human is able to choose the most appropriate exit. In that way, the so called clustering effect is observed (Helbing, Farkas, & Vicsek, Simulating Dynamical Features of Escape Panic, 2000). This is happening since humans are divided into groups: humans that select to exit from the first exit and other that leave the building from the other exit. The parameters of this environment are shown in Table 4, while snapshots of the experiment are shown in Figure 10.

Table 4 The parameters of evacuation scenario No. 3

Parameters	Values
$L_1(width)$	$20.0m$
$L_2(height)$	$20.0m$
N_H	99
$s(exits)$	2
$N_{1C_{i,j}} = \frac{L_1}{0.4}$	50 cells
$N_{2C_{i,j}} = \frac{L_2}{0.4}$	50 cells
$N_{C_{i,j}} = N_{1C_{i,j}} \times N_{2C_{i,j}}$	50×50 cells
$Obstacles$	Yes
$t(Time\ Steps)$	59
$Real\ time$	$17.62s$

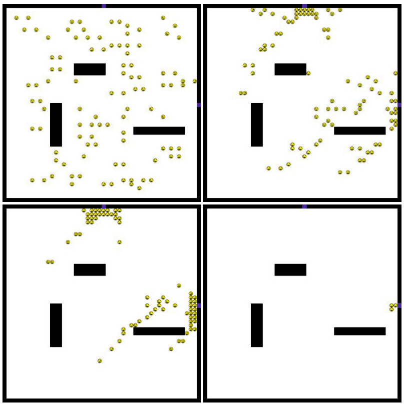

Fig. 10 Evacuation Scenario No. 3: An environment with 2 exits, 99 humans and some randomly placed obstacles

4.4 Experiment 4

In this evacuation scenario an environment with U shaped obstacles and three (3) adjacent located in the north side of the under study space exits is examined. The simulation of a scenario with U shaped obstacles is quite crucial, since humans may need to go in opposite direction of the exit in order to avoid the U-shaped obstacle. The parameters of this environment are shown in Table 5, while the images of the experiment are shown in Figure 11. As it can be observed, in this case scenario clogging effects at bottlenecks appear (Helbing, Farkas, & Vicsek, Simulating Dynamical Features of Escape Panic, 2000). However, the model is able to overcome such difficulties, given that humans evacuate successfully the place.

Table 5 The parameters of evacuation scenario No. 4

Parameters	Values
$L_1(width)$	$20.0m$
$L_2(height)$	$20.0m$
N_H	161
$s(exits)$	3
$N_{1C_{i,j}} = \frac{L_1}{0.4}$	50 cells
$N_{2C_{i,j}} = \frac{L_2}{0.4}$	50 cells
$N_{C_{i,j}} = N_{1C_{i,j}} \times N_{2C_{i,j}}$	50×50 cells
$Obstacles$	$U--shaped$
$t(Time\ Steps)$	69
$Real\ time$	$20.5s$

4.5 Experiment 5

In this evacuation scenario the space consists of multiple rooms. The rooms are the one inside the other and therefore humans should leave all rooms before reaching the exit of the space. The parameters of this environment are shown in Table 6 below, while the images of the experiment are shown in Figure 14. As it can be observed, in this case scenario clogging and arching effects appear (Helbing, Farkas, & Vicsek, Simulating Dynamical Features of Escape Panic, 2000). The simulation results demonstrated in the following Figure 12 indicate the ability of the model to respond properly to such scenarios.

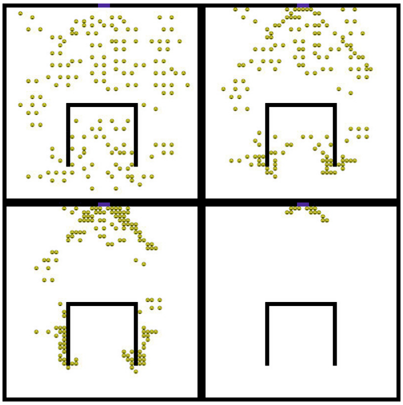

Fig. 11 Evacuation Scenario No. 4: A space with 3 consecutive exits and with a U - shaped obstacle

Table 6 The parameters of evacuation scenario No. 5

Parameters	Values
$L_1(width)$	$20.0m$
$L_2(height)$	$20.0m$
N_H	66
$s(exits)$	1
$N_{1C_{i,j}} = \frac{L_1}{0.4}$	50 cells
$N_{2C_{i,j}} = \frac{L_2}{0.4}$	50 cells
$N_{C_{i,j}} = N_{1C_{i,j}} \times N_{2C_{i,j}}$	50×50 cells
$Obstacles$	$walls$
$t(Time\ Steps)$	71
$Real\ time$	$21.2s$

Fig. 12 Evacuation Scenario No. 5: A space with internal rooms and 3 consecutive corresponding exits

5 Conclusions

In this chapter a bio–inspired crowd evacuation method based on CA and bio–mimicking Physarum's behaviour was described. The presented model take into account while mimicking the Physarum foraging process, the food diffusion, the organism's growth, the creation of tubes for each organism, the selection of optimum tube for each human in correspondence to the under study crowd evacuation and finally the movement of all humans at each time step towards near exit. The proposed evacuation model combines microscopic and macroscopic characteristics enabling the successful simulation of crowd evacuation taking into account key feature of evacuation of the places crowded by humans, like unity in diversity. In specific, several simulation scenarios were examined both in virtual indoor environments. The corresponding results have proven in a qualitative way the efficiency of the proposed model in terms of producing random to coherent motion of individuals due to common purpose, collective effects and blockings near exits in all the examined cases. Moreover, different behaviours during overcrowdness at one exit, as well as due to fire spreading, were successfully reproduced in some of the provided experiments.

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