Follow-the-Leader Cellular Automata Based Model Directing Crowd Movement

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Abstract. This paper describes a model that simulates crowd movement incorporating an efficient follow-the-leader technique based on cellular automata (CA). The scope of the method is to derive principal characteristics of collective motion of biological organisms, such as flocks, swarms or herds and to apply them to the simulation of crowd movement. Thus, the study focuses on the massive form of the movement of individuals, which is lastingly detected macroscopically, during urgent circumstances with the help of some form of guidance. Nevertheless, on a lower level, this formation derives from the application of simple local rules that are applied individually to every single member of the group. Hence, the adoption of CA-based formation has allowed the development of a micro-operating model with macro-features. Furthermore, the model takes advantage of the inherent ability of CA to represent sufficiently phenomena of arbitrary complexity. The response of the model has been evaluated through different simulation scenes that have been developed both in two and three dimensions.

Keywords: Cellular automata, Crowd movement, Follow-the-Leader.

1 Introduction

Safe crowd movement in case of emergency involves the immediate and fast redirection of individuals. Urgent instances vary from small to large scale ones. The first category includes mass departure from a building due to bomb or fire threat. The second one takes place in metropolitan areas due to mass catastrophes, such as heavy floods or earthquakes. Focusing on movements inside a building, the process is more likely to be completed successfully in case that some characteristics accommodate the activation of appropriate routes. Such features could be structural, e.g. multiple exits, alarms, sound and optical signals or human-based, e.g. guidance provided by well skilled personnel.

Algorithmically, it is desirable the development of a generic approach that could be applied to a variety of different cases. Plans of facing emergent circumstances are developed in order to reassure the most effective movement of people away from the

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G.C. Sirakoulis and S. Bandini (Eds.): ACRI 2012, LNCS 7495, pp. 752–762, 2012.

dangerous area. Thus, for each different case, a corresponding critical, temporal boundary is defined. Such boundaries can be effectively derived from appropriate simulation schemes. The latter are developed on the basis of computational models that try to emulate behaviours under emergent conditions.

According to the method that has been adopted, the crowd is approached as comprised individuals that follow their own rules of behaviour. In the past, crowd was modeled as homogeneous mass characterised by properties of a moving fluid. The main constraint was the large number of required computations. Nowadays, the advanced capabilities of computational systems sidestepped such difficulties. A step forward towards a more effective modeling of such processes is the incorporation of intelligent computational techniques, such as Cellular Automata [1].

Furthermore, it is a distinct feature of moving processes people to act together as forming a compound set. The, so called, herding or swarm or flocking behaviour arises, especially, in cases of emergency. Then people tend not to move autonomously but prefer to move in groups also due to psychological factors. In Physics, a flock is defined as the coherent motion of a group of self-propelled particles emerging from a simple set of interactions between the constituents of that group [2]. Flocking behaviour was initially simulated in 1986 by C.W. Reynolds [3]. He introduced the notion of boids, which are defined as self-propelled particles that have the ability to move according to a predefined set of rules. The initial pattern was created to emulate the behaviour of birds that form swarms but it can also be applied in cases of fishes or other biological organisms that present similar behaviours. In 1995, Vicsek et al. introduced the notion of flocking in the community of physicists by developing a model that presented physical mechanisms. This resulted in the creation of flocking formations [4]. They proved that a group of self-propelled particles, which is modeled with the use of a simple set of parameters, presents behaviour similar to that of a ferro-magnetic system. Airline companies have also applied routing methods of airplanes based on ants' behaviour and the theory of swarm intelligence [5]. Furthermore, in marketing, principles of flocking behaviour are used to explain the dependencies of human consuming tendencies [6].

The scope of this paper is to present a CA-based model that has been developed to simulate crowd movement deriving its theoretic principles from the collective behaviour of biological organisms (e.g. school of fishes, flock of birds etc). Although macroscopically, the individuals that form the crowd move like a mass towards a certain direction, the motion of each individual is independently adjusted by local rules. To that point, the adoption of CA approach allows the development of a microscopically-induced model with macroscopical characteristics. The driving mechanism of the model stems from two inter-dependent rules that are applied at different levels. At the local level of the restrained neighbourhood, individuals move towards the closest free cell that may lead to an exit. At a broader level each individual tries to stay bonded to other members of the crowd, in order not to be isolated. In literature, similar systems are called follow-the-leader systems and highlight the role of leaders in the evacuation. Though crowd evacuation simulation has been thoroughly investigated recently, little research focuses on simulating the evacuation process with Leader-Follower models [7], [8].

2 Related Work

Many different simulation approaches of crowd dynamics have been reported in the literature. Thus, methods based on CA are presented [9-11] as well as lattice-gas and social force models [12]. There are also fluid-dynamic [13] and agent-based [14] models or methods related to game theory [15] and experiments with animals [16]. In some models, pedestrians are considered as homogeneous individuals, whereas in others, they are treated as heterogeneous groups. There are methods that describe pedestrian dynamics in a microscopic scale, thus collective phenomena emerge from the complex interactions among individuals. There are also approaches that model crowd dynamics on a macroscopic scale. Moreover, there are models discrete in space and time and others spatial-temporally continuous.

Further focusing on CA, literature reports also a variety of CA-based models investigating crowd behaviour. CA based methods model human behaviours, such as inertial effects, unadventurous effect and group effect [17] or treat pedestrians as particles subject to long-range forces [18]. Furthermore, the impact of environmental conditions [19] and bi-directional pedestrian behaviour [20] has been studied with the use of CA as well as interactions among pedestrians, friction effects [21] and herding behaviour [12].

The presented model introduces the concept of a dynamically defined leader that is perceived as an exit by all other individuals. Thus, they adapt their movement towards the leader-exit. The idea of a leader as a moving exit facilitates the movement of a crowd towards a specific target, as for example towards an exit during evacuation. The leader itself follows a given strategy; it moves towards the nearest exit. The flexibility in the definition of the leader further accommodates the movement of the crowd. In case that a given leader is blocked or another member of the group moves faster then the role of the leader passes to another entity. Hence, the movement of the group is prevented from possible limitations.

3 Model Description

3.1 Basic Structure

A CA-based computational model has been developed that simulates the movement of a crowd formed by individuals, following some of the basic principles of [22]. The driving mechanism of the model is based on the assumption that each member of the crowd moves independently. Whenever possible, a group of individuals approaches the closest exit following the shortest route. Thus, each member is supposed to have a complete knowledge of the space topology and acts completely rational.

According to the CA modeling structure, the space is divided into rectangular parts that correspond to the cells of the lattice. The state of the cell is described by a value that is assigned to it from a predefined set of values. Specifically, value 0 (zero) indicates an empty cell, while value 1 (one) an occupied one. Value 2 (two) is assigned to cells that correspond to a part of a wall or an obstacle and value 3 (three) represents an exit. The structure of the algorithm is based on two arrays *start* and *final.* They represent the state of each cell at the beginning and at the end of each time step respectively. Assuming that the limits of the space correspond to walls, the boundary conditions of the CA model are constant. The simulation mechanism of the model is matrix-driven, discretising a floor area into a grid. The grid of the automaton is homogeneous and isotropic, whereas the CA cells are able to exist in two possible states; either free or occupied by exactly one particle. Each cell corresponds to the minimum area that a person could occupy [9]. During each time step, an individual chooses to move in one of the eight possible directions of its closest neighbourhood. Each particle moves towards the direction that is closer to an exit.

3.2 Crowd Movement in Two- or Three-Dimensions

The model has been developed to simulate crowd movement both in two- and three-dimensions, according to flocking principles and incorporating the Follow-the Leader technique. Results presented by J. Tourma et al. have also been taken under consideration [23]. As soon as a single member of the group is assigned the role of the leader, all other individuals adapt their moving attributes to the leaders'. Specifically, all other members try to follow the route of the leader by executing similar movements, thus forming and maintaining the collective pattern.

Following nature's practice, the model allows dynamical transitions of the role of the leader among the members of the group. Particularly, in case that a member of the group appears in front of the leader also following the same direction of movement, then a leader's role transition occurs. The member in front becomes the leader, whereas the leader turns into a simple member. An individual follows the leader until it reaches the target, e.g. the exit. Furthermore, the model enables the creation of different groups in the crowd, assigning to each group a leader and the corresponding members. It favors the dynamic grouping rather than the static one [8]. Instead of forming inflexible groups, the members of each group may change as the process evolves. Besides, dynamic grouping is more realistic than static.

Algorithmically, the model adopts a method of movement similar to closest-exit method. In fact, its functionality is extended by incorporating leaders as well. A value greater than value three (3) that has been used to indicate an exit is assigned to a cell that is occupied by a leader. Thus the leader is also treated as an exit as well, which a group of individuals tries to approach. Furthermore, alike the motion of a school of fishes in a fishbowl, the model is able to simulate the case of movement in a blocked (or non-exit) area. Hence, another one parameter is assigned to the leader, the internal clock. According to the value of the clock the leader makes a predefined movement. For example, the clock of a leader can be assigned values in the space of [1, 200]. Particularly, when the value of the clock lies in-between [1, 49], the leader moves to the North, [50, 99] to the West, [100, 149] to the South and [150,200] to the East respectively, thus defining an anti-clockwise route.

As far as the members of the group concern, their movement is defined by the same set of rules as the one that defines the movement of individuals towards an exit.

The new property that has been incorporated in the model relies on the fact that now the members of a group perceive their leader as a moving exit that they want to approach. This attribute enables the formation of the group and its persistence, without any computational overhead. In the case of the simplified simulation process, the velocities of the members have been adopted as unary. Hence, individuals can hardly pass their leader. Though, the model is provided with the option of an increased velocity of the leader.

From a mathematical point of view, the direction of movement of the individuals relies on a potential field. It derives from the negative gradient of a function that involves the distance (Manhattan) of each point of the area from the position of the leader. In the case of two-dimensions, the function $f(x,y)$ is defined as follows:

$$f(x,y) = abs(x - x_o) + abs(y - y_o) \tag{1}$$

where (x_o, y_o) correspond to the coordinates of the leader.

The corresponding gradient of the function $f(x,y)$ is defined as:

$$\begin{aligned} -\nabla f(x,y) &= -\left(\frac{\partial f(x,y)}{\partial x} \vec{i} + \frac{\partial f(x,y)}{\partial y} \vec{j} \right) \\ -\nabla f(x,y) &= -\left(\frac{\partial abs(x - x_o)}{\partial x} \vec{i} + \frac{\partial abs(y - y_o)}{dy} \vec{j} \right) \end{aligned} \tag{2}$$

It can be thought of as a collection of vectors pointing in the direction of decreasing values of $f(x,y)$.

Spatially, the whole process is divided in eight sub-sections, i.e. for the case that the leader moves i) downwards ($y>y_o$), ii) upwards ($y<y_o$), iii) to the left ($x>x_o$), iv) to the right ($x<x_o$), v) downwards and to the right ($y>y_o$) and ($x<x_o$), vi) downwards and to the left ($y>y_o$) and ($x>x_o$), vii) upwards and to the left ($y<y_o$) and ($x>x_o$) and viii) upwards and to the right ($y<y_o$) and ($x<x_o$). For instance, in the case that the leader moves downwards and to the right (i.e. case (v)), the corresponding potential field that is derived from equation (2), is depicted in Fig. 1.

Moreover, an additional modification has taken place, as far as obstacles concerns. In general, the leaders tend to move in sectors rather than following an internal clock. The latter is only adopted in the special case of a totally blocked area (fishbowl case). Thus, the movement of the leaders turns out to be more flexible and the obstacles' avoidance becomes more effective. Particularly, the two-dimensional space has been divided in 17 sectors (16 peripherals and a central one) and the leaders move among these sectors (Fig. 2). In the case of a clockwise movement, the sectors' changing sequence is 1-2-3-4-..-15-16-1, whereas the sequence becomes 16-15-…-2-1-16 to realise the anti-clockwise movement. The way that the leader moves depends on its value. In the case that the value is divided exactly with 2 then the leader moves clockwise, otherwise the leader moves anticlockwise.

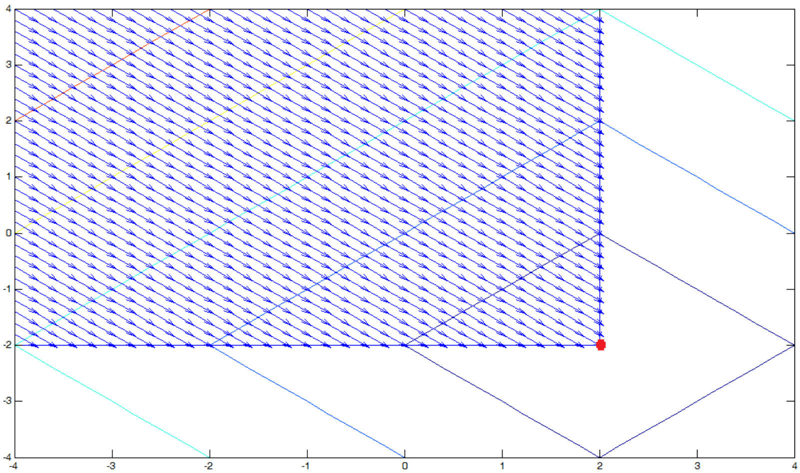

Fig. 1. The corresponding potential field in the case that the leader is positioned at (x_o=2, y_o=-2) and moving downwards and to the right. All individuals within blue-arrows area follow the leader (red spot).

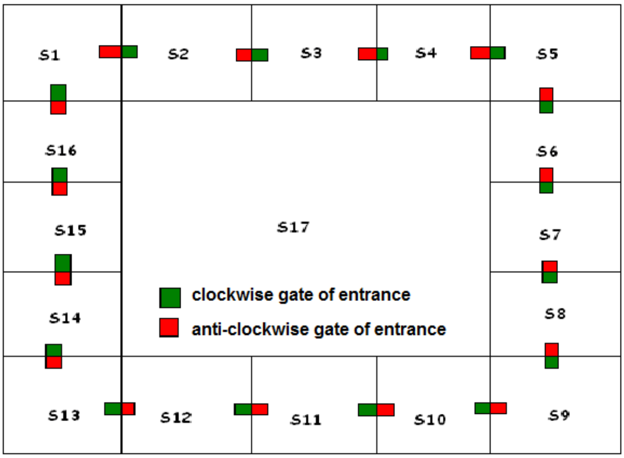

Fig. 2. Planar sections and gates of sections. For example, green gate that lies inside section 2 is used by leaders that tend to move from section 1 towards section 2. As soon as the leader enters section 2 starts to move towards green gate that lies inside section 3 (clockwise).

The adoption of sectors is based on the simple fact that even in real life bounded areas are divided to multiple sub-areas with their own formation and their own exits. Each sub-area shares the same properties with the total area, thus enabling the use of the property of the superposition. Hence, the scalability of the method is reassured, allowing its application in more complicated areas.

The movement of the leaders through sections takes place as follows: depending on the direction of the leaders' motion, each section is supplied with two gates that the leaders use to enter the section. The leaders move towards the exits following the same rules that the members of the flock use to follow the leader; they calculate the Manhattan distance of all neighbouring cells and choose to move towards the neighbouring cell, which is closer to the exit and it is not occupied as well. In a sense, whenever the leader lies in a section, it is attracted by the gate of the successive section. In case that also an obstacle exists in the area, the leader tries to avoid it by moving towards a close free cell. Provided that all neighbouring cells are occupied, this is not possible. Then another member of the group is defined as leader. The same process is repeated, until a member that is free to move towards the gate of the next section is defined as leader. A significant property that is attributed to the gates enables the movement of the leaders through the sections; the gate of reference of a section resides at the next section, which the leader tends to move towards. Hence, as soon as the leader approaches the gate, it is already inside the new section, i.e. inside the field of action of the next gate.

In three dimensions, the CA is defined in a cubic space, the dimensions of which are variable. They can be defined each time by the user, taking into consideration that each cell needs three coordinates (*i, j, k*) to be properly defined. The neighbourhood of each cell is shaped by its 26 closest cells, whereas there are four (4) sectors that divide the space in four rectangular parallelepipeds (Fig. 3a). In case that we wish to test the behavior of the model in 3-d dimensions, the following scheme takes place; the leaders pass through the sectors following the 1-2-3-4-1 sequence for the clockwise direction or 4-3-2-1-4 for the anti-clockwise one. Adopting similar logic as in two-dimensions, the gate that influences one sector lies inside the following sector. The gates are placed at the center of the internal sides of the sectors (Fig. 3b).

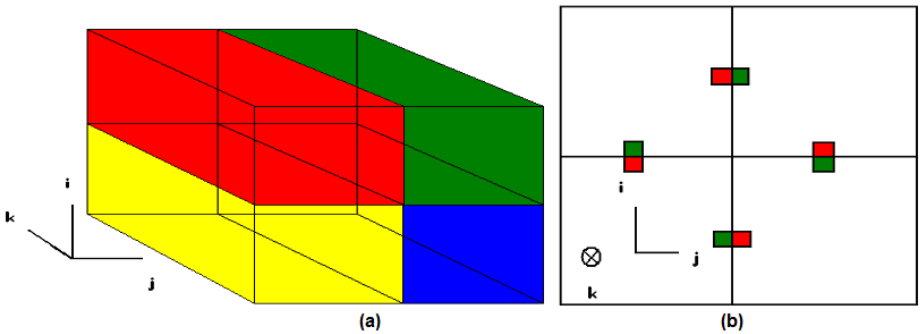

Fig. 3. (a) Four sectors in 3-D (b) Gates placed at the center of the internal sides of the sectors

4 Simulation Results

In order to validate the proposed model and evaluate its functionality a couple of different simulation schemes took place. The first one studied the case of obstacle avoidance. Solid obstacles were spread within the area of movement. It was observed that whenever a flock met an obstacle, it was divided into two smaller flocks that moved along the obstacle and they were unified again at the back of the obstacle. This is a response identical to nature's response. According to the second scheme, the leaders were forced to move faster than the members of the flock. The response of the model proved that even under such conditions, the members of the flock try to follow the leader, as it is naturally expected.

Furthermore, in all scenarios members of a flock were free to move from one flock to another. Thus, for example, in the case that two flocks approached each other very closely or a member of a flock could not follow its initial group, individuals tended to change groups. This is also a natural response that further validates the operation of the proposed model. The initial two-dimensional approach included a scheme with two groups of people that make a circling movement, each following a leader. The leaders initially followed the same direction and then moved to reverse directions in order the behaviour of the flocks to appear when they met each other. When moving reversely, there was a time span that the two groups merged until they separated again, each following its direction. The latter is also an expectable behaviour that is naturally defined. In all simulations, individuals moved within a restrained area with the walls forming the boundaries, thus adopting zero boundary conditions. Below, characteristic simulation scenarios are demonstrated that contain all above discussed attributes of crowd movement.

4.1 Two Leaders Move in Opposite Directions

This scenario includes two leaders moving in an opposite direction and it has taken place in 120 time steps. One group follows a leader that moves clockwise and another one trails a leader that moves anti-clockwise. This simulation has taken place so as the behaviour of two flocks in direction of collision to be studied. As the leaders approach each other, the two flocks follow the same direction until they merge (Fig. 4b). While the two leaders continue to move in opposite directions, the two groups divide again (Fig. 4c,d) depicting a behaviour that is also apparent in nature. This result enforces the efficiency of the model. In the meanwhile, some members of the first group have been incorporated into the other and vice versa. Such a transition is naturally expectable as well. Finally, as derived by the simulation process, the density of the crowd increases as the group turns in order to change its direction of motion. The latter observation is also confirmed by real life experiences.

4.2 Two Leaders Move in an Area with Obstacles

This scenario includes two leaders moving in an area with obstacles and it has taken place in 80 time steps. It demonstrates the way that the groups react when facing an obstacle that hinders their route. In any case, each group tries to follow its leader. Furthermore, depending on the area layout, a group may overcome an obstacle by moving along its perimeter or it may squish itself, adapting its shape to the free area between two obstacles (Fig. 5). Macroscopically, the flock adopts characteristics of a fluid, though the emerging behaviour derives from simple rules that they are applied locally. Finally, the simulation process affirms that the speed of the group decreases as it moves in an area that its members have to overcome obstacles.

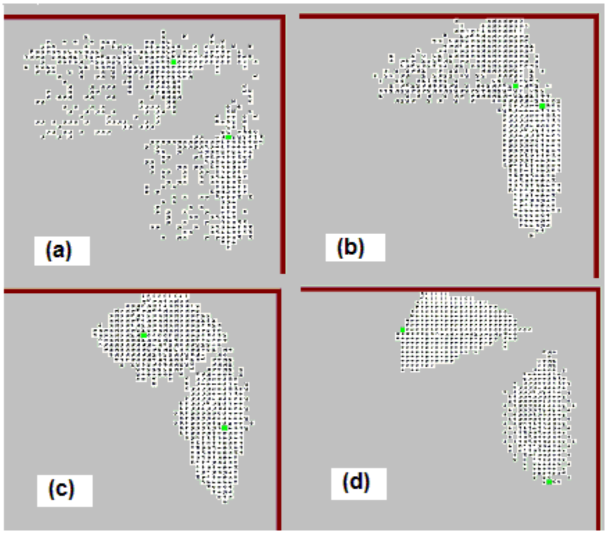

Fig. 4. Two leaders move in opposite directions. The two flocks that follow the leaders meet (a), merge (b) and split again after having passed the one through the other (c, d), respectively.

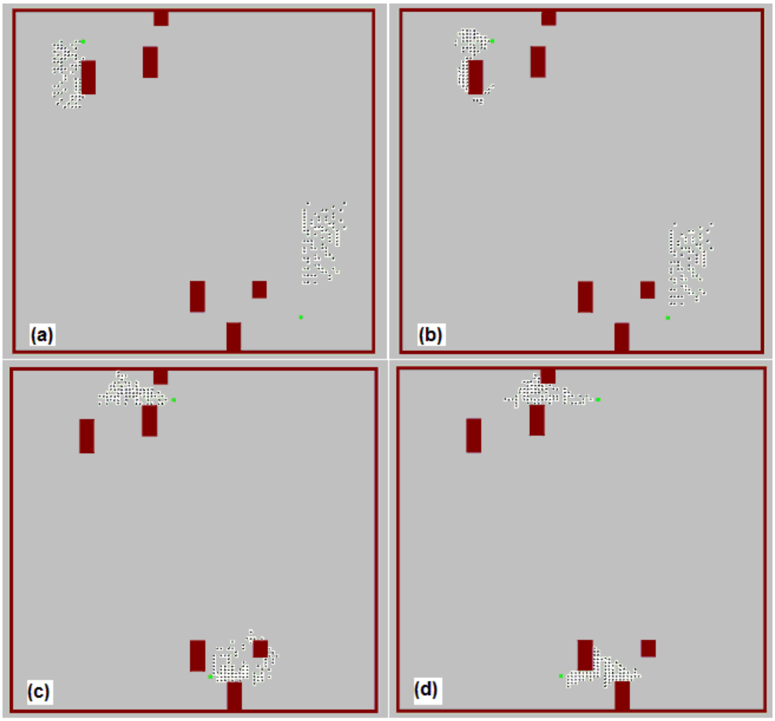

Fig. 5. Two leaders move among obstacles. The corresponding groups try to follow the leaders. Thus, they may move along the perimeter of an obstacle (a, b), or even squish themselves to move among obstacles (c, d).

5 Conclusions and Future Work

A CA-based computational model has been presented that aims at simulating qualitatively crowd behaviour. Particularly, various simulation scenarios demonstrated distinct features of crowd movement, thus enhancing the efficiency of the model. There have been presented phenomena such as flocking, increasing crowd density in turnings and crowd movement deceleration as self-organised groups try to pass obstacles. Furthermore, significant features of crowd dynamics, such as transition from a random to a coordinated motion during crowd movement as well as arching in front of exits have also been detected during simulations. Considerable modifications in crowd movement are observed when crowd density fluctuates, as congestions may lead to immobility. Such behaviour is also apparent during simulations, further validating the response of the model.

The driving mechanism of the model could be referred as biologically-inspired, since it derives from a naturally detected behaviour of biological organisms, i.e. follow-the-leader behaviour. The latter technique has been incorporated into the model and triggers the herding formations of crowd during mass collective motion. This lastingly detected macroscopical behaviour of crowds, especially during urgent circumstances, has been modeled on a lower level. It took place with the development of a CA and the application of simple local rules that define the moving options of every single member that forms the crowd. The number of acquired leaders is not fixed and depends on the layout of the evacuation area as well as on the dense of the crowd.

The serial access of array-structures that is adopted by the computational resources constraints the response of the model, especially as far as its depiction potentialities concerns. Undesirable co-ordinations appear when individuals move towards certain directions. Such problems could be moderated by adopting the use of parallel programming or parallel processing. The latter can be implemented with a graphical processing unit (GPU). Such a solution could enable a more effective utilisation of the intrinsic parallel characteristics of CA. Such a modification could certainly accelerate the response of the model and improve it qualitatively.

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