An Agent Model of Pedestrian and Group Dynamics: Experiments on Group Cohesion

Stefania Bandini[1,2], Federico Rubagotti[1], Giuseppe Vizzari[1,2], and Kenichiro Shimura[3]

[1] Complex Systems and Artificial Intelligence (CSAI) research center, Università degli Studi di Milano - Bicocca, Viale Sarca 336/14, 20126 Milano, Italy
{bandini,vizzari}@csai.disco.unimib.it, f.rubagotti@campus.unimib.it
[2] Crystal Project, Centre of Research Excellence in Hajj and Omrah (Hajjcore), Umm Al-Qura University, Makkah, Saudi Arabia
[3] Research Center for Advanced Science & Technology, The University of Tokyo, Japan
shimura@tokai.t.u-tokyo.ac.jp

Abstract. The simulation of pedestrian dynamics is a consolidated area of application for agent–based based models; however generally the presence of groups and particular relationships among pedestrians is treated in a simplistic way. This work describes an innovative agent–based based approach encapsulating in the pedestrian's behavioural model effects representing both proxemics and a simplified account of influences related to the presence of groups in the crowd. The model is tested in a simple scenario to evaluate the effectiveness of mechanisms to preserve groups cohesion maintaining a plausible overall crowd dynamic.

1 Introduction

Crowds of pedestrians can be safely considered as complex entities; various phenomena related to crowds support this statement: pedestrian behaviour shows a mix of competition for the space shared and collaboration due to the (not necessarily explicit) social norms; the dependency of individual choices on the past actions of other individuals and on the current perceived state of the system (that, in turn, depends on the individual choices of the comprised agents); the possibility to detect self-organization and emergent phenomena. The definition of models for explaining or predicting the dynamics of a complex system is a challenging scientific effort; nonetheless the significance and impact of human behaviour, and especially of the movements of pedestrians, in built environment in normal and extraordinary situations motivated a prolific research area focused on the study of pedestrian and crowd dynamics. The impact the results of these researches on activities of architects, designers and urban planners is apparent (see, e.g., [1] and [2]), especially considering dramatic episodes such as terrorist attacks, riots and fires, but also due to the growing issues in facing the organization and management of public events (ceremonies, races, carnivals, concerts, parties/social gatherings, and so on) and in designing naturally crowded places

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(e.g. stations, arenas, airports). These research efforts led to the realization of commercial, off-the-shelf simulators often adopted by firms and decision makers to elaborate what-if scenarios and evaluate their decisions with reference to specific metrics and criteria.

Cellular Automata have been widely adopted as a conceptual and computational instrument for the simulation of complex systems (see, e.g., [3]); in this specific context several CA based models (see, e.g., [4,5]) they have been adopted as an alternative to particle-based approaches [6], and they also influenced new approaches based on autonomous situated agents (see, e.g., [7,8,9]). The main aim of this work is to present an approach based on reactive autonomous situated agents derived by research on CA based model for pedestrian and crowd dynamics for a multidisciplinary investigation of the complex dynamics that characterize aggregations of pedestrians and crowds. This work is set in the context of the Crystals project[1], a joint research effort between the Complex Systems and Artificial Intelligence research center of the University of Milano–Bicocca, the Centre of Research Excellence in Hajj and Omrah and the Research Center for Advanced Science and Technology of the University of Tokyo. The main focus of the project is to investigate how the presence of heterogeneous groups influences emergent dynamics in the context of the Hajj and Omrah. This point is an open topic in the context of pedestrian modeling and simulation approaches: the implications of particular relationships among pedestrians in a crowd are generally not considered or treated in a very simplistic way by current approaches. In the context of the Hajj, the yearly pilgrimage to Mecca, the presence of groups (possibly characterized by an internal structure) and the cultural differences among pedestrians represent two fundamental features of the reference scenario.

The paper breaks down as follows: the following Sect. introduces the agent–based pedestrian and crowd model considering the possibility of pedestrians to be organized in groups, while Sect. 3 summarizes the results of the application of this model in a simple simulation scenario. Conclusions and future developments will end the paper.

2 The GA-Ped Model

The Group–Aware Pedestrian (GA- Ped) model is a reactive agents based model characterized by an environment that is discrete both in space and in time. The model employs floor fields (see, e.g., [10]) to support pedestrian navigation in the environment. In particular, each relevant final or intermediate target for a pedestrian is associated to a floor field, a sort of gradient indicating the most direct way towards the associated point of interest. Our system is represented by the triple: $Sys = \langle Env, Ped, Rules \rangle$ whose elements will be now introduced.

[1] `http://www.csai.disco.unimib.it/CSAI/CRYSTALS/`

2.1 Space and Environment

The representation of the space in our model is derived from the Cellular Automata theory: space is discretized into small cells which may be empty or occupied by exactly one pedestrian. At each discrete time step it is possible to analise the state of the system by observing the state of each cell (and, consequently, the position of each pedestrian into the environment). The environment is defined as $Env = \langle Space, Fields, Generators \rangle$ where the *Space* is a physical, bounded bi-dimensional area where pedestrians and objects are located; the size of the space is defined as a pair of values$(xsize, ysize)$ and it is specified by the user. In our model we consider only rectangular-shaped scenarios (but it is possible to shape the scenario defining non-walkable areas). The space in our model is modeled using a three-layer structure: $Space = \langle l_1, l_2, l_3 \rangle$ where each layer represents details related to a particular aspect of the environment. Each layer is a rectangular matrix sharing the same size of the other two. The first layer (l_1), contains all the details about the geometry of the environment and the properties of each cell. A cell may be a generating spot (i.e. a cell that can generate new pedestrians according to the simulation parameter), and can be walkable or not. A cell is thus characterized by a $cellID$, an unique key for each cell, it can be associated to a *generator* if the cell can generate pedestrians, it can be walkable or not (e.g. the cell contains a wall). The *second layer*, denoted as l_2, contains information about the values of the floor fields of each cell. Values are saved as pairs $(floorID, value)$. Data saved into the second layer concerns targets and the best path to follow to reach them. The *third layer*, l_3, is made up of cells that may be empty or occupied by one pedestrian. This layer stores the position of each pedestrian.

Generators and Targets – Information about generators and targets are saved into the first and second layer. A target is a location in the environment that the pedestrians may desire to reach. Examples of targets in a train station are ticket machines, platforms, exits and so on. A traveller may have a complex schedule composed of different targets like: (a) I have to buy a ticket, then (b) I want to drink a coffee and (c) reach platform number 10 to board the train to Berlin. This plan can be translated in the following schedule: (i) ticket machine, (ii) lounge, (iii) platform 10. From now on the words *schedule* and *itinerary* are used interchangeably. We will describe how pedestrians will be able to move towards the target later on.

Generators are cells that, at any iteration, may generate new pedestrians according to predetermined rules. *Generating spots* are groups of generator cells located in the same area and driven by the same set of rules of generation. In our model a *generating spots* is defined as $spot = \langle spotID, maxPed, positions, groups\ itineraries, frequency \rangle$ where *spotID* is an identifier for the generator; $maxPed$ is the maximum amount of pedestrians that the spot can generate during the entire simulation; *positions* indicate the cells belonging to that generating spot (a spot in fact may contain different cells); *groups* being the set of group types that can be generated, each associated with a frequency of generation; *itineraries* that can be assigned to each pedestrian, considering the fact that group members share the same schedule but that different groups may have different schedules, each associated with a frequency; $frequency$ is a value between 0 and 100, specifying the frequency of pedestrian generation (0 means never generate pedestrians, 100 means generate pedestrians at each iteration, if free space is available and if the desired maximum density has not been reached.).

Information about generators are stored in the first layer, on the contrary, targets are represented in the second layer, specified with their floor field values. In fact, every target has a position and it is associated to a floor field that guides pedestrians to it.

Floor Fields – As stated previously, the floor field can be thought of as a grid of cells underlying the primary grid of the environment. Each target has a floor field and the values are saved into the $l2$ of the environment. A floor field contains information suggesting the shortest path to reach the destination. In our model each cell contains information about every target defined in the model. Given the cell at position (x, y), the corresponding floor field values are saved into l_2, the content of $l_2(c_{x,y})$ is a list of pairs with the following structure: $(floorID, value)$. Values of a floor field are integers between 0 (no indication on how to reach the target) and 256 (target is present in the cell); the value of a floor field decreases when the distance from the target grows (e.g. according to the Manhattan distance). The GA-Ped model only comprises *static* floor fields, specifying the shortest path to destinations and targets. Interactions between pedestrians, that in other models are described by the use of *dynamic floor fields*, in our model are managed through a perception model based on the idea of *observation fan*, which will be introduced in Section 2.2.

Time and Environment Update Type. Our model is a discrete-time dynamical system, and update rules are applied to all pedestrians following an update method called *shuffled sequential update* [11]. At each iteration, pedestrians are updated following a random sequence. This choice was made in order to implement our method of collision avoidance based on cell reservation. In the shuffled sequential update, a pedestrian, when choosing the destination cell, has to check if this cell has been reserved by another pedestrian within the same time step. If not, the pedestrian will reserve that cell, but moving into at the end of the iteration. If the cell is already reserved, an alternative destination cell can be chosen. Each iteration corresponds to an amount of time directly proportional to the size of the cells of the environment and to the reaction time: given a squared cell of $40 \times 40cm^2$, the corresponding timescale is approximately of $0.3sec$, obtained by transposing the empirically observed value of average velocity of a pedestrian, that is $1.3m/s$ to the maximal walking speed of one cell per time step.

2.2 Pedestrians

Pedestrians are modeled as simple reactive agents situated in a bidimensional grid. Each pedestrian is provided with some attributes describing details like group membership, ID, schedules. Each pedestrian is also endowed with a set of *observation fans* that determine how he sees and evaluates the environment. Attributes, internal state and environment influence the behavior of our pedestrians: a pedestrian can move in one of the cells belonging to its Moore neighborhood, and to any possible movement is associated a revenue value, called *likability*, representing the desirability of moving into that position given the state of the pedestrian.

Pedestrian Characterization – a pedestrian is characterized by a simple set of attributes and in particular $pedestrian = \langle pedID, groupID, schedule \rangle$ with *pedID* being an identifier for each pedestrian, *groupID* (possibly null, in case of individuals) the group the pedestrian belongs to and *schedule* a list of goals to be accomplished by the pedestrian (one of the above introduced itineraries).

Perception model – In the GA-Ped model every pedestrian has the capability to observe the environment around him, looking for other pedestrians, walls and objects by means of an *observation fan*. An *observation fan* can be thought as the formalization of physical perceptive capabilities combined with the evaluation of the perception of relevant entities: it determines how far a pedestrian can see and how much importance has to be given to the presence of obstacles and other pedestrians. An *observation fan* is defined as follows:

$$\zeta = \langle type, xsize, ysize, weight, xoffset, yoffset \rangle$$

Where *type* identifies the direction of the fan: it can be 1 for diagonal directions and 2 for straight directions (the fan has different shapes and it may be asymmetric). Sizes and offsets are defined as shown in figure 1. Sizes (*xsize* and *ysize*) define the maximum distance to which the pedestrian can see. The shape of the fan is influenced by both the direction and the sizes. The offsets are used to define if the pedestrian can see backward and the size of the lateral view (only type 2, see Fig 1.c). The parameter *weight* is a matrix of values $w_{x,y} \in \mathbb{R}_+$ defined in the interval $[0, 1]$. These values determine the relationship between the *thing* that has been observed and the distance (e.g. given a wall, its distance influences differently the movement of a pedestrian).

For each class of groups is possible to define multiple *observation fans*; each fan can be applied when evaluating walls, pedestrians belonging to the same group, to other groups or, lastly, to particular groups. For instance, this feature is useful when modeling situations like football matches: it is possible to define two classes of groups, one made of supporters of the first team and the other of supporters of the second team. Groups belonging to the first class will interact differently if dealing with other groups belonging to the first class or belonging to the second one.

Behavior and Transition Rules – The behavior of a pedestrian is represented as a flow made up of four stages: *sleep*, *context evaluation*, *movement evaluation*, *movement*. When a new iteration is started, each pedestrian is in a sleeping state. This state is the only possible in this stage, and the pedestrian does

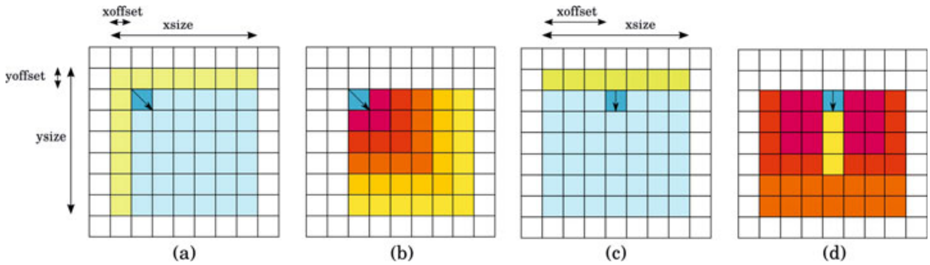

Fig. 1. Example of the shape of an observation fan for a diagonal direction (in this case south-east) and for a straight direction (in this case south): (a and c) in light cyan the cells that are observable by the pedestrian and are used for the evaluation, in green the observable backward area; (b and d) the weight matrix applied for the evaluation, in this case objects or pedestrians near the pedestrian have more weight that farther ones (e.g. this fan is useful for evaluating walls).

nothing but waits for a trigger signal from the system. The system wakes up each pedestrian once per iteration and, then, the pedestrian passes to a new state of context evaluation. In this stage, the pedestrian tries to collect all the information necessary to obtain spatial awareness. When the pedestrian has collected enough data about the environment around him, it reaches a new state. In this state behavioral rules are applied using the previously gathered data and a movement decision is taken. When the new position is notified to the system, the pedestrian returns to the initial state and waits for the new iteration.

In our model, pedestrian active behavior is limited to only two phases: in the second stage pedestrians collect all the information necessary to recognize the features of the environment around him and recall some data from their internal state about last actions and desired targets. A first set of rules determine the new state of the pedestrian. The new state, belonging to the stage of movement evaluation, depicts current circumstances the pedestrian is experiencing: e.g. the situation may be normal, the pedestrian may be stuck in a jam, it may be compressed in a dense crowd or lost in an unknown environment (i.e. no valid floor field values associated to the desired destination). This state of awareness is necessary to the choice of the movement as different circumstances may lead to different choices: a pedestrian stuck in a jam may try to go in the opposite direction in search for an alternative path, a lost pedestrian may start a random walk or look for other significant floor fields.

Pedestrian movement – Direction and speed of movement At each time step, pedestrians can change their position along nine directions (keeping the current position is considered a valid option), into the cells belonging to their Moore neighborhood of range $r = 1$. Each possible movement has a value called *likability* that determines how much the move is *good* in the terms of the criteria previously introduced. In order to keep our model simple and reduce complexity, we do not consider multiple speed. At each iteration a pedestrian can move only in the cells belonging to the Moore neighborhood, reaching a speed value of 1 or can maintain the position (in this case speed is 0)[2].

Functions and notation – In order to fully comprehend the pedestrian behavior introduced in the following paragraphs, it is necessary to premise the notational conventions and the functions we have introduced in our modelization:

- $c_{x,y}$ defines the cell with (valid) coordinates (x, y);
- $Floors$ is the set of the targets instantiated during the simulation. Each target has a floor field and they share the same *floorID* (i.e. with $t \in Floors$ we define both the target and the associated floor field);
- *Groups* the set containing the *groupID* of the groups instantiated during the simulation dynamics;
- $Classes$ is the set containing all the group classes declared when defining the scenario;
- *Directions* is the set of the possible directions. Are nine, defined using cardinal directions: $\{N, NE, E, SE, S, SW, W, NW, C\}$.

Given $x \in [0, xsize - 1]$ and $y \in [0, ysize - 1]$, we define some functions useful to determine the characteristics and the status of the cell $c_{x,y}$:

cell walkability, function $l_1(c_{x,y})$: this function determines if the cell $c_{x,y}$ is walkable or not (e.g. if there is a wall). If the cell is walkable the function returns the value 1, otherwise it returns 0. We assume that this function does not depend on time (i.e. the structure of the environment does not change during the simulation).

floor field value, function $l_2(c_{x,y}, t)$: this function determines the value of the floor field t in the cell $c_{x,y}$.

presence of pedestrians belonging to a given group, function $l_3(c_{x,y}, g)$: this function determines if in the cell $c_{x,y}$ contains a pedestrian belonging to a particular group g specified as input. If a pedestrian belonging to that group is contained in the cell, the function returns 1, otherwise it returns 0.

In addition to these functions, we also define the **observation fan** as $\zeta_{x,y,d}$, the set of cells that are observable according to the characteristics of the observation fan ζ, used by a pedestrian located in the cell at coordinates (x, y) and looking in the direction d.

The overall *likability* of a possible solution can be thought as the desirability of one of the neighboring cells. The more a cell is desirable, the higher is the probability that a pedestrian will choose to move into that position. In our model the *likability* is determined by the evaluation of the environment and it is defined as a composition of the following sequence of characteristics: (i) *goal driven component*, (ii) *group cohesion*, (iii) *proxemic repulsion*, (iv) *geometrical repulsion*, (v) *stochastic contribution.*

Formally, given a pedestrian belonging to the group class $g \in Groups$, in the state $q \in Q$ and reaching a goal $t \in Floors$, the *likability* of a neighbouring

[2] Our pedestrians can move only to the cells with distance 1 according to the Tchebychev distance.

cell $c_{x,y}$ is defined as $li(c_{x,y})$ and is obtained evaluating the maximum benefit the pedestrian can achieve moving into this cell (following the direction $d \in Directions$) using the observation fan ζ for the evaluation. The value of the characteristics that influence the likability are defined as follows:

goal driven component: it is the pedestrian wish to quickly reach its destination and is represented with the floor field. Our model follows the least effort theory: pedestrians will move on the shortest path to the target which needs the least effort. This component is defined as $l_2(c_{x,y}, t)$: it is the value of the floor field in the cell at coordinates (x, y) for the target t;

group cohesion: it is the whish to keep the group cohese, minimizing the distances between the members of the group. It is defined as the pedestrians belonging to the same group in the observation fan ζ, evaluated according to the associated weight matrix:

$$\zeta(group, d, (x, y), g) = \sum^{c_{i,j} \in \zeta_{x,y,d}} w^{\zeta}_{i,j} \cdot l_3(c_{i,j}, g) \tag{1}$$

geometrical repulsion: it represents the presence of walls and obstacles. Usually a pedestrian wishes to avoid the contact with these object and the movement is consequently influenced by their position. This influence is defined as the presence of walls (located in layer l_1) inside the observation fan ζ, according to the weight matrix for *walls* specified in the same observation fan:

$$\zeta(walls, d, (x, y)) = \sum^{c_{i,j} \in \zeta_{x,y,d}} w^{\zeta}_{i,j} \cdot l_1(c_{i,j}) \tag{2}$$

proxemic repulsion: it is the repulsion due to presence of pedestrians, alone or belonging to other groups (e.g. strangers). A pedestrian whishes to maintain a *safe* distance from these pedestrians and this desire is defined as the sum of these people in the observation fan ζ, according to the weight matrix for the group of these pedestrians:

$$\zeta(strangers, d, (x, y), g) = \sum^{c_{i,j} \in \zeta_{x,y,d}} w^{\zeta}_{i,j} \cdot (1 - l_3(c_{i,j}, g)); \tag{3}$$

stochasticity: similarly to some traffic simulation models (e.g. [12]), in order to introduce more realism and to obtain a non deterministic model, we define $\epsilon \in [0, 1]$ as a a random value that is different for each *likability* values and introduces stochasticity in the decision of the next movement.

The overall *likability* of a movement is thus defined as follows:

$$\begin{aligned} li(c_{x,y}, d, g, t) = {} & j_w \zeta(walls, d, (x, y)) + j_f field(t, (x, y)) - \\ & j_g \zeta(group, d, (x, y), g) - j_n \zeta(strangers, d, (x, y), g) + \epsilon. \end{aligned} \tag{4}$$

Group cohesion and floor field are positive components because they positively influence a decision as a pedestrian wishes to reach the destination quickly, keeping the group cohese at the same time. On the contrary, the presence of obstacles and other pedestrians has a negative impact as a pedestrian usually tends to avoid this contingency. The formula 4 summarizes the evaluation of the aspects that characterize the *likability* of a solution. A pedestrian for each possible movement *opens* an observation fan and examines the environment in the corresponding directions, evaluating elements that may make that movement opportune (e.g. the presence of other pedestrians belonging to the same group or an high floor field value and data that may discourage as the presence of walls or pedestrians belonging to other groups).

3 Simulation Scenario

The simulated scenario is a rectangular corridor, $5m$ wide and $10m$ long. We assume that the boundaries are open and that walls are present in the north and south borders. The width of the cells is $40cm$ and the sizes of the corridor are represented with 14 cells and 25 cells respectively. Pedestrians are generated at the east and west borders and their goal is to reach the opposite exit.

Group dispersion – Since we are simulating groups of pedestrians, observing how different group sizes and overall densities affect the dispersion of groups through their movement in the environment is a central issue of our work. We considered three different approaches to the definition of such a metric: (i) dispersion as an area, (ii) dispersion as a distance from a centroid and (iii) dispersion as summation of the edges of a connected graph. The formulas of group dispersion for each approach are defined as follows:

$$\text{(a) } \Xi(C)^{I} = \frac{\mathrm{A}_C}{|C|} \qquad \text{(b) } \Xi(C)^{II} = \frac{\sum_{i=1}^{|C|} d(c,p_i)}{|C|} \quad \text{(c) } \Xi(C)^{III} = \frac{\sum_{i=1}^{|E|} w(e_i)}{|V|}$$

where C is the group of pedestrians (each member is enumerated using the notation p_i), A_C is its area, c as the centroid of the group, d is defined as the euclidean distance in $\mathbb{R}^2$ and $v_i \in V$ is a set of vertices (each pedestrian is a vertex) of a connected graph $G = \{V, E\}$. We tested the approaches using a set of over fifty different configurations of groups, representatives of significant situations for which we have an intuitive idea of the degree of dispersion of comprised groups.The results highlighted that the first and third approaches capture complementary aspects of our intuitive idea of dispersion, while the second one provides results similar to the third. We decided to combine the first and third approaches by means of a linear combination, allow obtaining a fairly unbiased measurement of dispersion. First of all, we normalized the metrics in the closed range $[0, 1]$ using the function $\Xi(C) = (\tanh(\Xi(C)^{\frac{1}{\eta}}))^{\varpi}$, with Ξ as the value generated by one of the three metrics previously introduced, and ϖ, η as normalization parameters. Then we combined two approaches in the following metric:

$$\overline{\Xi}(C) = \Xi(C)^{I}w^{I} + \Xi(C)^{III}w^{III}, \tag{5}$$

this function returns values the real range $[0, 1]$, with two weights w^I and w^{III} such that $w^I + w^{III} = 1$. In the preovious formula $\Xi(C)^I$ is the normalized value of the group dispersion for the group C, obtained with the first metric and $\Xi(C)^{III}$ the value obtained with the third metric.

Large group vs small group counterflow – We were interest in studying the dynamics of friction and avoidance that are verified when two groups with different size, traveling in opposite directions, are facing each others in a rectangular shaped corridor. We simulated the $5m \times 10m$ corridor with one large group traveling from the left (west) to the right (east), opposed to one small group traveling in the opposite direction. The aim of this particular set up was to investigate the differences in the dispersion of the smaller group with respect of the size of the large group and the overall time necessary to walk through the corridor. From now on we call the small group as the *challenging* group and the large group as the *opponent* group.

We considered opponent group of five different sizes: 10, 20, 30, 40 and 50. Challenging groups were defined with only two sizes: 3 and 5. The results are consistent with the observable phenomena as the model can simulate all the three possible cases that can be spotted in the real world: (i) the challenging group remains compact and moves around the opponent group; (ii) one or more members of the challenging group moves around the larger group in the other side with respect to the other members of the group; (iii) one or more members of the challenging group remain stuck in the middle of the opponent group and then the small group temporarily breaks up.

It is also interesting to point out that in our model, if a split is verified in the challenging group, when their members overcome the opponent group, they aim to form again a compact configuration. The actual size of the simulation scenario is however too small to detect this *reforming* of the group[3]. Figure 2 presents screenshots of the simulation at different time steps. It is possible to observe the range of different circumstance that our model is able to simulate: for example, in the simulation #3 the challenging groups can overcome the opponent one simply by moving around it, the same situation is represented in simulation #1 but the challenging group experiences more friction generated by the opponents. Simulations #2 and #4 show a challenging group that splits in two and their members moving around the opponent group on both the two sides. We investigated the relationships between the time necessary to the members of the challenging group to reach the opposite end of the corridor in relation with the size of the opponent group. As expected, and in tune with the previous observations, the larger the size of the opponent group, the higher time necessary to the members of the challenging group to reach their destination is. The difference of size in the challenging group only slightly influences the performances: it is

[3] We carried out additional simulations in larger environments and we qualitatively observed the group re-union.

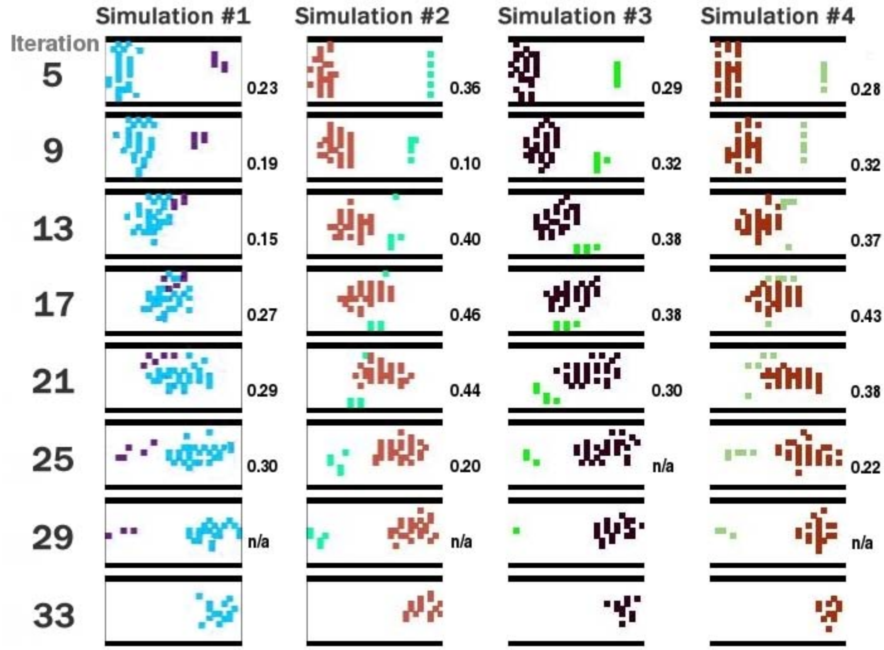

Fig. 2. Images representing the state of the simulation taken at different time steps. The opponent group is composed of 30 pedestrians, while the challenging group size is 5. The small number on the right of each state is the dispersion value of the challenging group.

easier to remain stuck in the opponent group but the difference between three and five pedestrians is insufficient to obtain significant differences.

Dispersion in counterflow – In addition to verifying the plausibility and validity of the overall system dynamics generated by our model [13], we tried to evaluate qualitatively and quantitatively the effectiveness of mechanism preserving group cohesion. We investigated the relationship between the the size of the opponent group and the average dispersion of the challenging group. As expected, the larger the size of the opponent group, the higher the dispersion of the challenging group is. This happens mainly for two reasons: (i) it is easier for the challenging group to remain stuck in the middle of a spatially wide opponent group and (ii) if the challenging group splits in two, the separation between the two sub-groups when moving around is higher. We also observed that small groups are more stable as they can maintain their compactness more frequently. It is also interesting to focus the attention on the high variability of plausible phenomena our model is able to reproduce: increasing the size of the opponent group usually increases the friction between the two groups and the consequently the possibility that the challenging group loses its compactness is higher. It is interesting to notice that there are situations in which dispersion does not present a monotonic behavior: in simulation #4 (Fig. 2) the challenging group firstly disperses, splitting in two parts, but eventually re-groups.

4 Conclusions and Future Developments

The paper presented an agent based pedestrian model considering groups as a fundamental element influencing the overall system dynamics. The model adopts a simple notion of group (i.e. a set of pedestrians sharing the destination of their movement and the tendency to stay close to each other) and it has been applied to a simple scenario in which it was able to generate plausible group dynamics, in terms of preserving when appropriate the cohesion of the group while also achieving a quantitatively realistic pedestrian simulation. Validation against real data is being conducted and preliminary results show a promising correspondence between simulated and observed data.

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