Pedestrian Dynamics in Presence of Groups: an Agent-Based Model Applied to a Real World Case Study

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ABSTRACT

The paper introduces an agent-based model for the simulation of crowds of pedestrians whose main innovative element is the representation and management of an important type of social interaction among the pedestrians: members of groups, in fact, carry out of a form of interaction (by means of verbal or non-verbal communication) that allows them to preserve the cohesion of the group even in particular conditions, such as counter flows, presence of obstacles or narrow passages. The paper formally describes the model and presents its application to a real world scenario in which an analysis of the impact of groups on the overall observed system dynamics was performed. The simulation results are compared to empirical data and they show that the introduced model is able to produce quantitatively plausible results in situations characterised by the presence of groups of pedestrians.

Categories and Subject Descriptors

I.6 [**Simulation and Modeling**]: Applications

General Terms

Experimentation

Keywords

pedestrian and crowd modeling, interdisciplinary approaches

1. INTRODUCTION

The simulation of pedestrians and crowds is a consolidated and successful application of research results in the more general area of computer simulation of complex systems. Relevant contributions to this area come from disciplines ranging from physics and applied mathematics to computer science, often influenced by anthropological, psychological, sociological studies. The quality of the results provided by simulation models was sufficient to lead to the design and development of commercial software packages, offering useful functionalities to the end user (e.g. CAD integration, CAD-like functionalities, advanced visualisation and analysis tools) in addition to a simulation engine[1]. Pedestrian models can be roughly classified into three main categories that respectively consider pedestrians as *particles subject to forces*, particular *states of cells* in which the environment is subdivided in Cellular Automata (CA) approaches, or *autonomous agents* acting and interacting in an environment. The most widely adopted particle based approach is represented by the *social force model* [9], which implicitly employs fundamental proxemic concepts like the tendency of a pedestrian to stay away from other ones while moving towards his/her goal. *Cellular Automata* based approaches have also been successfully applied in this context: in particular, the floor-field model [5], in which the cells are endowed with a discretised gradient guiding pedestrians towards potential destinations. Finally, works like [10] essentially extend CA approaches, separating the pedestrians from the environment and granting them a behavioural specification that is generally more complex than what is generally represented in terms of a simple CA transition rule, but they essentially adopt similar methodologies. The resulting models are *agent–based*, since pedestrians are not merely states of cell. Relevant recent innovative studies employing agent-based approaches regard higher level aspects of pedestrian behaviour, like social aspects and the transfer of emotions in crowds (see, e.g., [4]) and they are not necessarily related to a discrete spatial representation of the simulated environment.

A recent survey of the field by [18] and by a report commissioned by the Cabinet Office by [6] made clear that, even after the substantial research that has been carried out in this area, there is still much room for innovations in models improving their performances both in terms of *effectiveness* in modelling pedestrians and crowd phenomena, in terms of *expressiveness* of the models (i.e. simplifying the modelling activity or introducing the possibility of representing phenomena that were still not considered by existing approaches), and in terms of *efficiency* of the simulation tools. Research on models able to represent and manage phenomena still not considered or properly managed is thus still lively and important. One of the aspects of crowds of pedestrians that has only been recently considered is represented by the implications of the presence of groups. A small number of recent works represent a relevant effort towards the modeling of groups, respectively in particle-based [15] (extending the social force model), in CA-based [17] (with ad-hoc approaches) and in agent-based approaches [16] (intro-

[1]See `http://www.evacmod.net/?q=node/5` for a large list of pedestrian simulation models and tools.

ducing specific behavioral rules for managing group oriented behaviors): in all these approaches, groups are modeled by means of additional contributions to the overall pedestrian behaviour representing the tendency to stay close to other group members. However, the above approaches only mostly deal with small groups in relatively low density conditions; those dealing with relatively large groups (tens of pedestrians) were not validated against real data. The last point is a crucial and critical element of this kind of research effort: computational models represent a way to formally and precisely define a computable form of theory of pedestrian and crowd dynamics. However, these theories must be validated employing field data, acquired by means of experiments and observations of the modeled phenomena, before the models can actually be used for sake of prediction. This paper represents a step in this direction, since it reports the results of a field observation and analysis of pedestrian and group behaviour (in the following section) then it introduces a model for pedestrian simulation encompassing an adaptive model for the preservation of group cohesion (Sect. 3) that is finally applied in a virtual counterpart of the observed scenario. Results of this simulation campaign are discussed in Sect. 4. Conclusions and future developments end the paper.

2. FIELD DATA ABOUT GROUPS

This Section comprises several empirical studies aimed at investigating pedestrian crowd dynamics in the natural context by using on-field observation. In particular the survey was aimed at studying the impact of grouping and proxemics behaviour on the whole crowd pedestrian dynamics. Data analyses were focused on: (i) *level of density and service*, (ii) *presence of groups* within the pedestrian flows, (iii) *trajectories and walking speed* of both singles and group members. Furthermore the *spatial dispersion* of group members while walking was measured in order to propose an innovative empirical contribution for a detailed description of group proxemics dynamics while walking.

The survey was performed the last 24$^{\text{th}}$ of November 2012 from about 2:50 pm to 4:10 pm. It consisted in the observation of the bidirectional pedestrian flows within the Vittorio Emanuele II gallery, a popular commercial-touristic walkway situated in the Milan city centre (Italy). The gallery was chosen as a crowded urban scenario, given the large amount of people that pass through it during the weekend for shopping, entertainment and visiting touristic-historical attractions in the centre of Milan.

The team performing the observation was composed of four people. Several preliminary inspections were performed to check the topographical features of the walkway. The balcony of the gallery, that surrounds the inside volume of the architecture from about ten meters in height, was chosen as location thanks to possibility to (i) position the equipment for video footages from a quasi-zenithal point of view and (ii) to avoid as much as possible to influence the behaviour of observed subjects, thanks to a railing of the balcony partly hiding the observation equipment. The equipment consisted of two professional full HD video cameras with tripods. The existing legislation about privacy was consulted and complied in order to exceed ethical issues about the privacy of the people recorded within the pedestrian flows.

Two independent coders performed a manual data analyses, in order to reduce errors by crosschecking their results. A square portion of the walkway was considered for data analysis: 12.8 meters wide and 12.8 meters long (163.84 square meters). In order to perform data analyses, the inner space of the selected area was discretised in cells by superimposing a grid[2] on the video (see Fig. 1); the grid was composed of 1024 squares 0.4 meters wide and 0.4 meters long. The video and the annotation data will soon be made available only for research purposes through the web.

2.1 Level of Density and Service

The bidirectional pedestrian flows (from North to South and vice versa) were manually counted minute by minute: 7773 people passed through the selected portion of the Vittorio Emanuale II Gallery from 2:50 pm to 4:08 pm. The average level of density within the selected area (defined as the quantitative relationship between a physical area and the number of people who occupy it) was detected considering 78 snapshots of video footages, randomly selected with a time interval of one minute. The observed average level of density was low (0.22 people/squared meter). Despite it was not possible to analyse continuous situations of high density, several situation of irregular and local distribution of high density were detected within the observed scenario.

According to the Highway Capacity Manual by [14], the level of density in motion situation was more properly estimated taking into account the bidirectional walkway level of service criteria: counting the number of people walking through a certain unit of space (meter) in a certain unit of time (minute). The average level of flow rate within the observed walkway scenario belongs to a B level (7.78 ped/min/m) that is associated with an irregular flow in low-medium density condition.

2.2 Flow Composition

The second stage of data analysis was focused on the detection of groups within the pedestrian flows, the number of group members and the group proxemics spatial arrangement while walking. The identification of groups in the streaming of passerby was assessed on the basis of verbal and nonverbal communication among members: visual contact, body orientation, gesticulation and spatial cohesion among members. To more thoroughly evaluate all these indicators the coder was actually encouraged to rewind the video and take the necessary time to tell situations of simple local (in time an space) similar movements, due to the contextual situation, by different pedestrians from actual group situations. The whole video was sampled considering one minute every five: a subset of 15 minutes was extracted and 1645 pedestrians were counted (21.16% of the total bidirectional flows). Concerning the flow composition, 15.81% of the pedestrians arrived alone, while the 84.19% arrived in groups: 43.65% of groups were couples, 17.14% triples and 23.40% larger groups (composed of four or five members). Large structured groups, such as touristic committees, that were present in the observed situation, were analysed considering sub-groups.

[2]The grid was designed using *Photoshop CS5* (according to the perspective of the video images). An alphanumeric code was added on the sides of the grid. Finally, the grid with a transparent background was superimposed to a black-white version of the video images by means of *iMovie*. To perform counting activities, the video was reproduced by using *VLC* player thanks to its possibility to playback the images in slow motion and/or frame by frame and to use an extension time format that included hundredths of a second.

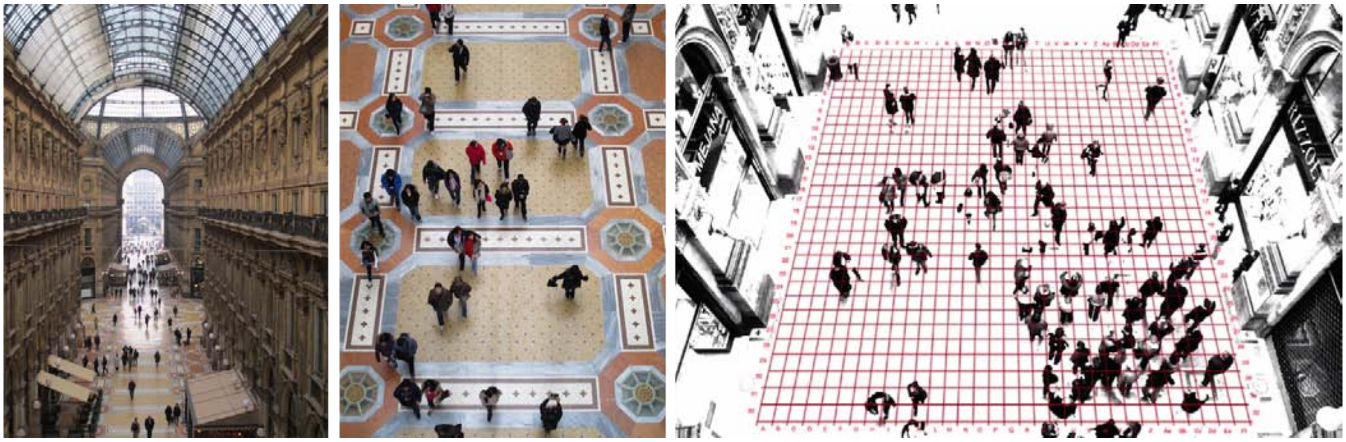

Figure 1: From the left: an overview of the Vittorio Emanuele II gallery, the streaming of passerby within the walkway and a snapshot of the recorded video images with the superimposed grid for data analysis

2.3 Trajectories and Walking Speed

The walking speed of both singles and group members was measured considering the path and the time to reach the ending point of their movement in the monitored area (corresponding to the centre of the cell of the last row of the grid) from the starting point (corresponding to the centre cell of the first row of the grid). Only the time distribution related to the *B* level of service was considered (as mentioned, the 59% of the whole video footages), in order to focus on pedestrian dynamics in situation of irregular flow. A sample of 122 people was randomly extracted: 30 singles, 15 couples, 10 triples and 8 groups of four members. The estimated age of pedestrians was approximately between 15 and 70; groups with accompanied children were not taken into account for data analyses. About gender, the sample was composed of 63 males (56% of the total) and 59 females (44% of the total). Differences in age and gender were not considered in this study. The selected pedestrians were chosen among those not stopping at shops' windows or entering shops, to actually focus on movement dynamics and not on the choice of activities (like in the vein of [8]).

The alphanumeric grid was used to track the trajectories of both single and group members within the walkway and to measure the length of their path[3] (considering the features of the cells: 0.4 m wide, 0.4 m long).

A first analysis was devoted to the identification of the length of the average walking path of singles (M=13.96 m, ±1.11), couples (M=13.39 m, ± 0.38), triples (M=13.34 m, ± 0.27) and groups of four members (M=13.16 m, ± 0.46). Then, the two tailed t-test analyses were used to identify differences in path among pedestrian. Results showed a significant difference in path length between: singles and couples (p value<0.05), singles and triples (p value<0.05), singles and groups of four members (p value<0.05). No significant differences were detected between path length of couples and triples (p value>0.05), triples and groups of four members (p value>0.05), couples and groups of four members (p value>0.05). The results showed that the path of singles is 4,48% longer than the average path of group members (including couples, triples and groups of four members).

The walking speed of both singles and group members was detected considering the path of each pedestrian within the flows and the time to reach the ending point from their starting point. A first analysis was devoted to the identification of the average walking speed of singles (M=1.22 m/s, ± 1.16), couples (M=0.92 m/s, ± 0.18), triples (M=0.73 m/s, ± 0.10) and groups of four members (M=0.65 m/s, ± 0.04). Then, the two tailed t-test analyses were used to identify differences in walking speed among pedestrian. Results showed a significant difference in walking speed between: singles and couples (p value<0.01), singles and triples (p value<0.01), singles and groups of four members (p value<0.01), couples and triples (p value<0.01), triples and groups of four members (p value< 0.05). In conclusion, the results showed that the average walking speed of group members (including couples, triples and groups of four members) is 37.21% lower than the walking speed of singles.

The correlated results about pedestrian path and speed showed that in situation of irregular flow singles tend to cross the space with more frequent changes of direction in order to maintain their velocity, avoiding perceived obstacles like slower pedestrians or groups. On the contrary, groups tend to have a more stable overall behaviour, adjusting their spatial arrangement and speed to face the contextual conditions of irregular flow: this is probably due to (i) the difficulty in coordinating an overall change of direction and (ii) the tendency to preserve the possibility of maintaining cohesion and communication among members.

2.4 Group Proxemics Dispersion

In order to improve the understanding of pedestrian proxemics behaviour the last part of the study is focused on the dynamic spatial dispersion of group members while walking. The dispersion among group members was measured as the summation of the distances between each pedestrian and the centroid (the geometrical centre of the group) all

[3]To measure the walking path and speed we considered each pedestrian as a point without mass in a two-dimensional plane. By using the alphanumeric grid, we considered the cell occupied by the feet of each pedestrian as its own actual position. The starting and final steps were measured from the half of the cell, consequently 0.2 m is the corresponding length of the each related path; any diagonal step cell by cell was measured as the diagonal between the two cells (0.56 m); any straight step was measured as the segment between the centre of two cells (0.4 m).

normalised by the cardinality of the group. The centroid was obtained as the arithmetic mean of all spatial positions of the group members, considering the alphanumeric grid. In order to find the spatial positions, the trajectories of the group members belonging to the previous described sample (15 couples, 10 triples and 8 groups of four members) were further analysed. In particular, the positions of the group members were detected analysing the recorded video images every 40 frames (the time interval between two frames corresponds to about 1.79 seconds, according to the quality and definition of the video images) starting from the co-presence of the all members on the alphanumeric grid. This kind of sampling permitted to consider 10 snapshots for each groups.

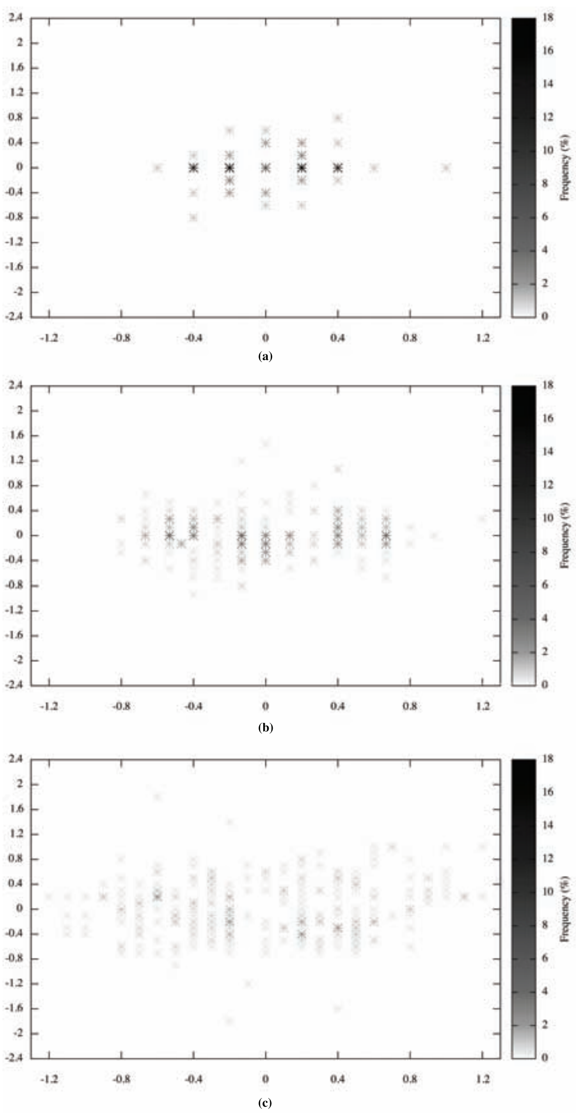

Figure 2: A diagram showing most frequent positions, normalised with respect to the centroid and the movement direction, assumed by members of couples (a), triples (b) and groups of four members (c).

A first analysis was devoted to the identification of the average proxemics dispersion of couples (M=0.35 m, ± 0.14), triples (M=0.53 m, ± 0.17) and groups of four members (M=0.67 m, ± 0.12). Then, the two tailed t-test analyses were used to identify differences in proxemics dispersion among couples, triples and groups of four members. Results showed a significant difference in spatial dispersion between: couples and triples (p value$<$0.05), couples and groups of four members (p value$<$0.01). No significant differences between triples and groups of four members (p value$>$ 0.05). In conclusion, the results showed that the average spatial dispersion of triples and groups of four members while walking is 40.97% higher than the dispersion of couples.

Starting from the achieved results about group proxemics dispersion, we finally focused on a quantitative and detailed description of group spatial layout while walking. The normalised positions of each pedestrian with respect to the centroid and the movement direction were detected by means of a sample of 10 snapshots for each groups (15 couples, 10 triple and 8 groups of four members) and then further analysed in order to identify the most frequent group proxemics spatial configurations, taking into account the degree of alignment of each pedestrian (see Figure 2). Result showed that couple members tend to walk side by side, aligned to the each other with a distance of 0.4 m (36% of the sample) or 0.8 m (24% of the sample), forming a line perpendicular to the walking direction (line abreast pattern); triples tend to walk with a line abreast layout (13% of the sample), with the members spaced of 0.60 m. Regarding groups of four members it was not possible to detect a typical spatial pattern: the reciprocal positions of group members appeared much more dispersed than in the case of smaller groups, probably to due the continuous arrangements in spatial positioning while walking.

3. PEDESTRIAN SIMULATION MODEL

In this section the formalisation of the agent-based computational model will be discussed, by focusing on the definition of its three main elements: *environment*, *update mechanism* and *pedestrian behaviour*.

3.1 Environment

The environment is modelled in a discrete way by representing it as a grid of 40 cm sided square cells size (according to the average area occupied by a pedestrian [20]). Cells have a state indicating the fact that they are vacant or occupied by obstacles or pedestrians: $State(c) : Cells \rightarrow \{Free,\ Obstacle,\ OnePed_i, TwoPeds_{ij}\}$.

The last two elements of the definition point out if the cell is occupied by one or two pedestrians respectively, with their own identifier: the second case is allowed only in a controlled way to simulate overcrowded situations, in which the density is higher than 6.25 pedestrians per square metre (i.e. the maximum density reachable by our discretisation).

The information related to the scenario[4] of the simulation are represented by means of *spatial markers*, special sets of cells that describe relevant elements in the environment. In particular, three kinds of spatial markers are defined: (i) *start* areas, that indicate the generation points of agents in the scenario. Agent generation can occur in *block*,

[4]It represents both the structure of the environment and all the information required for the realization of a specific simulation, such as crowd management demands (pedestrians generation profile, origin-destination matrices) and spatial constraints.

all at once, or according to a user defined *frequency*, along with information on type of agent to be generated and its destination and group membership; (ii) *destination* areas, which define the possible targets of the pedestrians in the environment; (iii) *obstacles*, that identify all the non-walkable areas as walls and zones where pedestrians can not enter.

Space annotation allows the definition of virtual grids of the environment, as containers of information for agents and their movement. In our model, we adopt the *floor field* approach [5], that is based on the generation of a set of superimposed grids (similar to the grid of the environment) starting from the information derived from spatial markers. Floor field values are spread on the grid as a gradient and they are used to support pedestrians in the navigation of the environment, representing their interactions with static object (i.e., destination areas and obstacles) or with other pedestrians. Moreover, floor fields can be *static* (created at the beginning and not changed during the simulation) or *dynamic* (updated during the simulation). Three kinds of floor fields are defined in our model: (i) *path field*, that indicates for every cell the distance from one destination area, acting as a potential field that drives pedestrians towards it (static). One path field for each destination point is generated in each scenario; (ii) *obstacles field*, that indicates for every cell the distance from neighbour obstacles or walls (static). Only one obstacles field is generated in each simulation scenario; (iii) *density field*, that indicates for each cell the pedestrian density in the surroundings at the current time-step (dynamic). Like the previous one, the density field is unique for each scenario.

Chessboard metric with $\sqrt{2}$ variation over corners [13] is used to produce the spreading of the information in the path and obstacle fields. Moreover, pedestrians cause a modification to the density field by adding a value $v = \frac{1}{d^2}$ to cells whose distance d from their current position is below a given threshold. Agents are able to perceive floor fields values in their neighbourhood by means of a function $Val(f, c)$ (f represents the field type and c is the perceived cell). This approach to the definition of the objective part of the perception model moves the burden of its management from agents to the environment, which would need to monitor agents anyway in order to produce some of the simulation results.

3.2 Pedestrians and Movement

Formally, our agents are defined by the following triple: $Ped = \langle Id, Group, State \rangle$; where $State = \langle position, oldDir, Dest \rangle$, with their own numerical identifier, their group (if any) and their internal state, that defines the current position of the agent, the previous movement and the final destination, associated to the relative path field.

Before describing agent behavioural specification, it is necessary to introduce the formal representation of the nature and structure of the groups they can belong to, since this is an influential factor for movement decisions.

3.2.1 Social Interactions

To represent different types of relationships, two kinds of groups have been defined in the model: a *simple group* indicates a family or a restricted set of friends, or any other small assembly of persons in which there is a strong and simply recognisable cohesion; a *structured group* is generally a large one (e.g. team supporters or tourists in an organised tour), that shows a slight cohesion and a natural fragmentation into subgroups, sometimes simple.

Members of a simple group it is possible to identify an apparent tendency to stay close, in order to guarantee the possibility to perform interactions by means of verbal or non-verbal communication [7]. On the contrary, in large groups people are mostly linked by the sharing of a common goal, and the overall group tends to maintain only a weak compactness, with a following behaviour between members. In order to model these two typologies, the formal representation of a group is described by the following: $Group : \langle Id, [SubGroup_1, \ldots, SubGroup_m], [Ped_1, \cdots, Ped_n] \rangle$.

In particular, if the group is simple, it will have an empty set of subgroups, otherwise it will not contain any direct references to pedestrians inside it, which will be stored in the respective leafs of its three structure. Differences on the modelled behavioural mechanism in simple/structured groups will be analysed in the following section, with the description of the utility function.

3.2.2 Agent Behaviour

Agent behaviour in a single simulation turn is organised into four steps: *perception, utility calculation, action choice* and *movement*. The *perception* step provides to the agent all the information needed for choosing its destination cell. In particular, if an agent does not belong to a group (from here called *individual*), in this phase it will only extract values from the floor fields, while in the other case it will perceive also the positions of the other group members within a configurable distance, for the calculation of the *cohesion* parameter. The choice of each action is based on an utility value assigned to every possible movement according to the function $U(c) = \frac{\kappa_g G(c) + \kappa_{ob} Ob(c) + \kappa_s S(c) + \kappa_c C(c) + \kappa_i I(c) + \kappa_d D(c) + \kappa_{ov} Ov(c)}{d}$.

Function $U(c)$ takes into account the behavioural components considered relevant for pedestrian movement, each one is modelled by means of a function that returns values in range $[-1; +1]$, if it represents an *attractive* element (i.e. its goal), or in range $[-1; 0]$, if it represents a *repulsive* one for the agent. For each function a κ coefficient has been introduced for its calibration: these coefficients, being also able to actually modulate tendencies based on objective information about agent's spatial context, complement the objective part of the perception model allowing agent heterogeneity. The purpose of the function denominator d is to constrain the diagonal movements, in which the agents cover a greater distance ($0.4 * \sqrt{2}$ instead of 0.4) and assume higher speed respect with the non-diagonal ones.

The first three functions exploit information derived by local floor fields: $G(c)$ is associated to goal attraction whereas $Ob(c)$ and $S(c)$ respectively to geometric and social repulsion. Functions $C(c)$ and $I(c)$ are linear cobinations of the perceived positions of members of agent group (respectively simple and structured) in an extended neighbourhood; they compute the level of attractiveness of each neighbour cell, relating to group cohesion phenomenon. Finally, $D(c)$ adds a bonus to the utility of the cell next to the agent according to his/her previous direction (a sort of *inertia* factor), while $Ov(c)$ describes the *overlapping* mechanism, a method used to allow two pedestrians to temporarily occupy the same cell at the same step, to manage high-density situations. Overlapping plays an important role in preserving overall pedestrian flow in medium-high density situations (density higher than 2 pedestrians per square metre) [2].

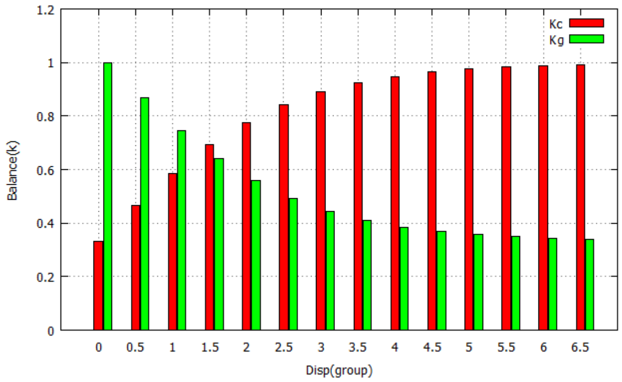

Figure 3: Graphical representation of $Balance(k)$, for $k = 1$ and $\delta = 2.5$.

As we previously said, the main difference between simple and structured groups resides in the cohesion intensity, which in the simple ones is significantly stronger. Functions $C(c)$ and $I(c)$ have been defined to correctly model this difference. Nonetheless, various preliminary tests on benchmark scenarios show us that, used singularly, function $C(c)$ is not able to reproduce realistic simulations. Human behaviour is, in fact, very complex and can react differently even in simple situation, for example by allowing temporary fragmentation of simple groups in front of several constraints (obstacles or opposite flows). Acting statically on the calibration weight, it is not possible to achieve this dynamic behaviour: with a small cohesion parameter several permanent fragmentations have been reproduced, while with an increase of it we obtained no group dispersions, but also an excessive and unrealistic compactness.

In order to face this issue, another function has been introduced in the model, to adaptively balance the calibration weight of the three attractive behavioural elements, depending on the fragmentation level of simple groups:

$$Balance(k) = \begin{cases} \frac{1}{3} \cdot k + (\frac{2}{3} \cdot k \cdot DispBalance) & \text{if } k = k_c \\ \frac{1}{3} \cdot k + (\frac{2}{3} \cdot k \cdot (1 - DispBalance)) & \text{if } k = k_g \vee k = k_i \\ k & \text{otherwise} \end{cases}$$

where $DispBalance = tanh(\frac{Disp(Group)}{\delta})$, $Disp(Group) = \frac{Area(Group)}{|Group|}$, k_i, k_g and k_c are the weighted parameters of $U(c)$, δ is the calibration parameter of this mechanism and $Area(Group)$ calculates the area of the convex hull defined using positions of the group members. Fig. 3 exemplifies both the group dispersion computation and the effects of the *Balance* function on parameters. The effective utility computation, therefore, employs calibration weights resulting from this computation, that allows achieving a dynamic and adaptive behaviour of groups: cohesion relaxes if members are sufficiently close to each other and it intensifies with the growth of dispersion.

After the utility evaluation for all the cells in the neighbourhood, the choice of action is stochastic, with the probability to move in each cell c as (N is the normalization factor): $P(c) = N \cdot e^{U(c)}$. On the basis of $P(c)$, agents move in the resulted cell according to their set of possible actions, defined as list of the eight possible movements in the Moore neighbourhood, plus the action to keep the position (indicated as X): $A = \{NW, N, NE, W, X, E, SW, S, SE\}$.

3.3 Time and Update Mechanism

In the basic model definition time is also discrete; in an initial definition of the duration of a time step was set to 0.31 s. This choice, considering the size of the cell (a square with 40 cm sides), generates a linear pedestrian speed of about 1.3 m/s, which is in line with the data from the literature representing observations of crowd in normal conditions [20], nonetheless we already implemented an extension of the model allowing the management of heterogeneous walking speeds [1].

Regarding the update mechanism, three different strategies are usually considered in this context [12]: *ordered sequential*, *shuffled sequential* and *parallel* update. The first two strategies are based on a sequential update of agents, respectively managed according to a *static* list of priorities that reflects their order of generation or a *dynamic* one, shuffled at each time step. The parallel update calculates instead the choice of movement of all the pedestrians at the same time, actuating choices and managing conflicts in a latter stage. The two sequential strategies imply a simpler operational management, due to an a-priori resolution of conflicts between pedestrians. For this work, we adopted the parallel update strategy, in accordance with the current literature, where it is considered much more realistic due to consideration of actual conflicts between pedestrians, arisen for the movement in a shared space [11].

With this update strategy, the agents life-cycle must consider that before carrying out the *movement* execution potential conflicts, essentially related to the simultaneous choice of two (or more) pedestrians to occupy the same cell, must be solved. The overall simulation step therefore follows a three step procedure: (i) *update of choices* and *conflicts detection* for each agent of the simulation; (ii) *conflicts resolution*, that is the resolution of the detected conflicts between agent intentions; (iii) *agents movement*, that is the update of agent positions exploiting the previous conflicts resolution, and *field update*, that is the computation of the new density field according to the updated positions of the agents.

The resolution of conflicts employs an approach essentially based on the one introduced in [11], based on the notion of friction. Let us first consider that conflicts can involve two of more pedestrians: in case more than two pedestrians involved in a conflict for the same cell, the first step of the management strategy is to block all but two of them, chosen randomly, reducing the problem to the case of a simple conflict among two pedestrians. To manage a simple conflict, another random number between 0 and 1 is generated and compared to two thresholds, $frict_l$ and $frict_h$, with $0 < frict_l < frict_h \leq 1$: the outcome can be that all agents are blocked when the extracted number is lower than $frict_l$, only one agent moves (chosen randomly) when the extracted number is between $frict_l$ and $frict_h$ included, or even two agents move when the number is higher than $frict_h$ (in this case pedestrian overlapping occurs). For our tests, the values of the thresholds make it quite relatively unlikely the resolution of a simple conflict with one agent moving and the other blocked, and much less likely their overlapping.

4. DISCUSSION OF TEST RESULTS

4.1 Configuration of the Simulation Scenario

LoS	Size	Av. Dispersion	Observed
A	2	0.336 ($\pm$ 0.157)	
	3	0.479 ($\pm$ 0.153)	
	4	0.575 ($\pm$ 0.146)	
B	2	0.351 ($\pm$ 0.174)	0.35 ($\pm$ 0.14)
	3	0.505 ($\pm$ 0.194)	0.53 ($\pm$ 0.17)
	4	0.609 ($\pm$ 0.210)	0.67 ($\pm$ 0.12)

Table 1: Average groups dispersion achieved by the simulations (standard deviation inside breaks).

LoS	Size	Av. Speed	Observed
A	1	1.19	
	2	1.115	
	3	1.119	
	4	1.11	
B	1	1.172	1.22
	2	1.107	0.92
	3	1.105	0.73
	4	1.099	0.65

Table 2: Average speeds of groups.

The environment is a discrete representation of the part of Vittorio Emanuele Gallery considered for the data extraction (see Sec. 2). It consists in a large corridor with size 12.8 m $\times$ 13.6 m. At each end, one *start area* is placed for the agents generation, respecting the frequency of arrival observed in the videos; corridor ends also comprise a destination area corresponding to the start area positioned on the other end. We decided not to consider the attractiveness of shops for two reasons: first of all, several shops in this section of the gallery are restaurants and they are not really much considered at the time of the observation, second the pedestrians selected for manual analysis did not stop at any shopping window. In order to reproduce the levels of service A and B we configured two different frequency profiles which lead to achieve, respectively, 30 and 50 pedestrians in the environment on average. The agent population comprises 15.8 % of individuals, while the remaining part is divided in groups of 2 (52%), 3 (20%) and 4 (28%) members, consistently with the observed composition of pedestrian population. In order to overcome biases caused by the simulation initialisation, for both density configurations, a set of 5 relatively short simulations (5 minutes of simulated time, for a total of 25 minutes of simulated time for both LOS conditions) has been run with different random seeds. Finally, simulations have been ran with the following configuration of the calibration weights: (i) utility function weights: $k_g = 8$, $k_{ob} = 2$, $k_s = 30$, $k_c = 6$, $k_I = 6$, $k_d = 2$ and $k_{ov} = 5$; (ii) cohesion mechanism: $\delta = 3.0$; (iii) friction weights: $frict_l = 0.8$, $frict_h = 0.96$.

4.2 Results

The data that can be gathered by means of a simulation covers a wide array of observable measurements. By means of this set of experiments, however, out main goal is the validation of reproduced behaviour of the agents inside groups, evaluating therefore the plausibility of the cohesion mechanism encompassed by the model.

The first measured data represents an indicator of the average dispersion of the different types of group during the simulation. Several methods have been proposed in the literature for describing the dispersion, since it is an intuitive concept that can however be formalised in different ways [3]. The results shown in Table 4.2 have been achieved by using the centroid method, describing dispersion as the average distance assumed by members of the group from its center of gravity, calculated as the average position of all the group members.

The results show that the cohesion mechanism is quite effective: the dispersion of groups in the two settings (LoS A and B) is similar and the increase of density have led to a very light increase of the average and standard deviation. The most important consideration, however, is the fact that these data are consistent with the empirically observed values (which refer to the B LOS conditions).

Table 4.2 shows instead the average speed characterising the movement of the different types of pedestrians (individuals or members of a certain type of group), calculated using the length of the actual trajectory and the time needed to move from the start area to any cell of the destination area of the corridor. In this case the model has only been able to reproduce results similar to the empirically observed data only for individuals and it only showed a slight decrease in the velocity of group members. On the other hand, it must be noted that all the agents have been configured with the same desired speed of 1.3 m/s, that is based on empirically observed velocity for pedestrians traveling for business purpose [19]. The same observation reports that pedestrians moving for leisure generally have a lower average walking speed. Therefore, our conjecture is that the much lower walking speed of groups might be due not only to the fact that members try to preserve the possibility to establish verbal and non-verbal communication, but also to a change in the reason and motivation for moving in the environment. Further analyses on this issue are object of future studies.

Finally, Table 4.2 analyses average travel distances covered by pedestrians in the simulations. This measure is obviously strictly related to the previous one, being actually used in the computation of the walking speed. As a consequence, even if simulated trajectories are very close to the measured ones also in this case the model was not able to differentiate paths covered by individuals and group ones (in some cases the traveled distance of individuals was actually lower, unlike in the observed data). In addition to the above considerations on motivations of the movement, that can also have an influence in the frequency of direction changes, we want to emphasise that a discrete model has intrinsic limits in the faithful reproduction of trajectories (that are inherently jagged and not as smooth as the real ones), so it could be difficult improving this kind of result adopting a discrete model.

5. CONCLUSIONS

This paper has introduced an empirical investigation of the influence of group presence in crowds of pedestrians by means of a field observation and a simulation campaign employing an agent-based model encompassing a specific adaptive mechanism for group behaviour in the same scenario. Empirical results achieved by the model are in tune with the

LoS	Size	Av. Distance	Observed
A	1	13.767 ($\pm$ 0.57)	
	2	13.922 ($\pm$ 0.621)	
	3	13.980 ($\pm$ 0.624)	
	4	14.052 ($\pm$ 0.653)	
B	1	13.857 ($\pm$ 0.577)	13.96 ($\pm$ 1.11)
	2	13.99 ($\pm$ 0.628)	13.39 ($\pm$ 0.38)
	3	14.049 ($\pm$ 0.654)	13.34 ($\pm$ 0.27)
	4	14.087 ($\pm$ 0.653)	13.16 ($\pm$ 0.46)

Table 3: Average travelled distance of groups.

actual observed data for the metrics related to group dispersion and walking trajectories. Nonetheless, additional work must be conducted to further understand if the lower speed of members of large groups is solely due to group influence or also to a change in the motivations of pedestrians, and therefore on their desired walking speed. Analogous considerations can be done for pedestrian trajectories although, in this case, the model is probably close to the intrinsic limits in the reproduction of smooth paths of any discrete approach.

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