PEDESTRIAN SOCIAL GROUPS MODELING & SIMULATION: A STATE OF THE ART

Elvezia Maria Cepolina[(a)], Federico Menichini[(a)]

[(a)] DICI - Department of Civil & Industrial EngineeringCollege of Engineering - University of Pisa

[(a)] e.cepolina@ing.unipi.it

ABSTRACT
The paper focuses on pedestrian social groups. A social group is formed by individuals that have social ties and intentionally walk together, such as friends or family members.
The percentage of people in social groups within a crowd is large. Pedestrian crowds have been studied, modeled and simulated for different purposes.
The simulation of crowds is employed to support pedestrian environment designs. It allows to elaborate "what if" scenarios and to evaluate the environment design with reference to specific criteria.
Virtual worlds, to become more lively and appealing, are populated by large number of characters. Typically, these characters should be able to navigate through the virtual environment in a human-like manner.
The study of pedestrian social groups plays a very important role also in the case these groups include mobile robots as individuals and as a robot team.

The papers presents empirical evidences of social group walking behavior. Then, briefly presents the most relevant pedestrian microscopic models, focusing on the ones that take into account social groups. A critical review of the current approaches and future developments end the paper.

Keywords: social groups, pedestrians, modeling, simulation, traffic, crowds

1. INTRODUCTION

The study of human crowd dynamics has recently found great interest in many research fields such as: the planning and design of the pedestrian environment; crowd safety during mass events; computer graphics and robot navigation.
Good pedestrian facilities promote people to walk, whilst poor ones discourage the use of area or structure where they are.This creates the necessity of measuring the performance of pedestrian facilities in order to determine quality of operations, existing deficiencies, needs for improvements, and for purposes of priority settings. Traditionally, the quality of operations of transportation facilities is assessed on the basis of the level of service (LOS) concept. These levels currently classify the level of comfort based on space available for movement and speed (and delay, in case of crosswalks). The comfort is assumed to be linked to the possibility to maintain a free space, during the motion, that every pedestrian requires around itself, and to maintain the desired speed. Therefore, assuming anhomogeneous pedestrian crowd, the LOS levelis assessed in terms of average characteristics of pedestrian flow, like average density and average speed. Guidance is provided for different area types and times of day (Sisiopiku et al. 2015).
In transportation studies attention has been paid also to walking spatial patternsand their impact on the overall traffic efficiency.Walking spatial patterns that influence crowd dynamics are related to "physics" of crowd motion such as:

- the organization around bottlenecks: the resulting zipper effect causes the capacity of the bottleneck to increase in a stepwise fashion with the width of the bottleneck (Hoogendoorn and Daamen 2005, Kretz et al. 2006),
- the segregation of opposite flows in pedestrian counterstreams: compared to a situation without counterflow the performance - in terms of passing or total times, speed, and flux - of a group of walkers is never reduced as much as one would expect from the amount of counterflow. This phenomenon can be summed up by saying that the sum of fluxes in a counterflow situation was always found to be larger than the flux in any of the no counterflow situations (Kretzet al. 2006, Moussaı¨et al. 2009, Helbing and Molnar 1995) or
- the turbulent movement in extremely dense crowds: the fundamental diagram has been reproduced for these situations and demonstrates that the average local flow is not reduced to zero at highly dense situations (Yu and Johansson 2007) .

All these studies investigated a crowd as a collection of isolated individuals, each having their own desired speed and direction of motion and social interactions among pedestrians have been largely neglected. Moussaid et al. (2010) focused on social interaction among pedestrians in crowd and investigated the spatial organization of walking pedestrian groups, in terms of average angle and distance between pedestrians, to find out whether there are any specific patterns of spatial group organization and how such patterns change with

increasing density. Crowd dynamics is not only determined by physical constraints induced by other pedestrians and the environment, but also significantly by communicative, social interactions among individuals.
One of the most relevant and at the same time most challenging problems are panic stampedes, which are a serious concern during mass events. Despite huge numbers of security forces and crowd control measures, hundreds of lives are lost in crowd disasters each year. The goal of many researches in this field is the identification of variables that are helpful for an advance warning of critical crowd conditions: these variables allow one to understand where and when crowd accidents tend to occur (Helbinget al. 2007). The identification of critical crowd conditions are important for the organization of safer mass events.
Field studies (Isobe et al. 2004, Kretz et al. 2006) have shown that in crowds, social group members do not communicate. Pedestrians follow other pedestrians without establishing a formal and steady social relationship (Fang J. et al. 2015).
Recent field work has shown that evacuees perform complex maneuvers and behave deliberately rather than in a non-cooperatively competitive manner or mindless panic. Some of these studies show that social and social-psychological factors significantly influence pedestrians' movement (Aguirre et al. 2011).
Algorithms that, based on surveillance trajectory data and informed by social psychological models of collective behavior, automatically discover small groups of individuals traveling together in a crowd have been proposed (Ge et al. 2012, Sochman et al. 2011). These algorithms could be used by police during public mass events to discover pathways or monitor for abnormal events and therefore to plan their intervention: rather than seeing an irrational homogeneous crowd, police should be looking at small groups, only a few of which might merit coercion.
In *computer graphics*the target is to create virtual worlds. Virtual worlds are ubiquitous in video games, training applications and animation films. Such worlds, to become more lively and appealing, are populated by large number of characters. Typically, these characters should be able to navigate through the virtual environment in a human-like manner. (Rojas et al.2016,Karamouzas and Overmars 2012)
Although state-of-the-art computer graphics enables a virtual reconstruction of the built environment with impressive geometric and photometric detail, it should enable the automated animation of the environment's human occupants (Badler et al. 1993). Human animation should be visual plausible rather than correct. The addition of groups can improve the plausibility of crowd scenarios (Peters et al. 2008).
Robot navigation should be smooth and safe in dynamic environments. If the obstacle is an intelligent agent, such as a human or another robot, this problem is complicated by the difficulty in predicting the agent's reaction to the robot's own movements. Dynamic obstacle avoidance is contingent on two separate capabilities. First, the robot must be able to predict the future trajectory of a dynamic obstacle passing through the robot's environment. Secondly, the robot must define a control strategy that is both optimized for the predicted trajectory and safe in any other outcome. Many approaches, inspired by human navigation in crowded pedestrian environments, draw from the sociology literature on pedestrian interaction (Knepper and Rus 2012). In navigating through personal spaces, humans make frequent, minor corrections to their trajectory in response to the predicted motions of other people. In so doing, we follow a social convention, or pedestrian bargain, designed to distribute responsibility for altering one's trajectory in recognition of another's intentions. Wolfinger (Wolfinger 1995) describes the pedestrian bargain as comprising two rules: "(1) people must behave like competent pedestrians, and (2) people must trust copresent others to behave like competent pedestrians". Algorithms for robot local navigation try to implement the same heuristics for mutual avoidance adopted by humans. In doing so, the resulting trajectories are human-friendly, because they can intuitively be predicted and interpreted by humans and the algorithms result suitable for the use on robots sharing navigation spaces with humans.
The paper focuses on pedestrian social groups. According to Hughes and Lee (2006), the term "group" is used here in its sociological sense: it is "a collection of individuals who have relations to one another that make them interdependent to some significant degree". A group is formed by individuals that have social ties and intentionally walk together, such as friends or family members.A social group is characterised by the duration of the interaction and the communicative setting.Social groupsrepresent an important component of urban crowds in low and medium density conditionswhilst in overcrowded environments the communication assumption between group members is not available anymore (Zhang et al. 2011).
We define temporary voluntary groups a group formed by several proximate pedestrians that voluntary walk temporary close to each otherin specific situations. There is not any social relationship between the group members. It has been observed that people are likely to follow others in front of them; they will walk on the same side of the path as other people in front of them and they will take avoidance action on the same side. This behavior leads to temporary voluntary groups

The paper breaks down as follows: the following section reports empirical evidences of social group walking behavior. Section 3 briefly presents the most relevant pedestrian microscopic models, focusing on the ones that take into account social groups. Section 4 ends the paper and includes a critical review of the current approaches and future developments.

2. EMPIRICAL KNOWLEDGE ON WALKING BEHAVIOUR OF PEDESTRIAN SOCIAL GROUPS

2.1. The frequency of social groups

Empirical studies show that in the real-world, large proportions of pedestrians are in social groups (Aveni 1977). The percentage of people in groups within a crowd ranges from 40% to 70%: the percentage changes according to different times and environment situations (Coleman and James 1961, Singh et al. 2009). Generally, more groups can be observed in leisure areas in public holidays (Moussaïd et al., 2010). According with Singhet al. (2009), in travelling environment (train station), the percentages of people in groups are about 55%; in shopping environments, the percentage is about 65%; on university campus where people study or work, the figure is about 47%. These data are reported in figure 1.

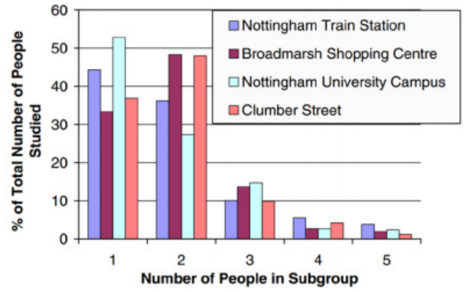

Figure 1: The sizes and proportions of subgroups within a crowd (Singh et al. 2009)

The reported % are not so far from other empirical evidences: in the data collected by Moussaı¨d et al (2010), up to 70% of observed pedestrians in a commercial street walked in group; in the data collected by Cepolina et al. in the “infinite” corridor in a building of Massachusetts Institute of Technology (Cepolina et al. 2016), about 42% walked in social groups.

Table 1:Dimensions of the observed social groups (Cepolina et al. 2016)

N. groups.	Groups of 2 ped.	Groups of 3 ped.	Groups of 4 ped.
59 (132 ped)	83% (49 groups - 98ped)	10 % (6 groups - 18 ped)	7 % (4 groups - 16 ped)

As it concerns the group dimensions, the data collected in this study are reported in table 1: the 83% of the total number of pedestrians that walk in groups, belongs to a 2 member group. The 10% of the total number of pedestrians that walk in groups, belongs to a 3 membergroup and the 7% of the total number of pedestrians that walk in groups, belongs to a 4 member group. Almost 45% of the groups were composed by both the genders. Among the mono gender groups, we observed an equal number of female and male groups.

The existence of ubiquitous social groups indicates that not only the individual-level, but also the group-level behaviour needs to be included in the modelling program in order to carry out realistic pedestrian simulations in low and medium density conditions.

2.2. Effects of group size on walking speed

As observed by Moussaı¨d et al (2010), pedestrian walking speeds decrease linearly with growing group size, as shown in figure 2.

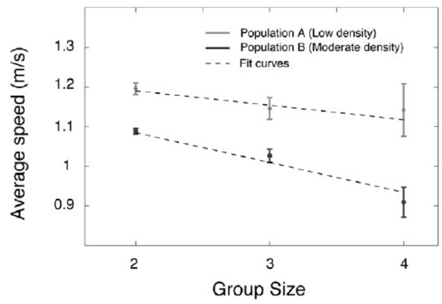

Figure 2: Effects of group size on walking speed (Moussaı¨d et al (2010))

Similar findings were discussed in the research of Schultz, et al. (2010), who recorded and analyzed the walking behavior of passengers in Dresden International Airport.

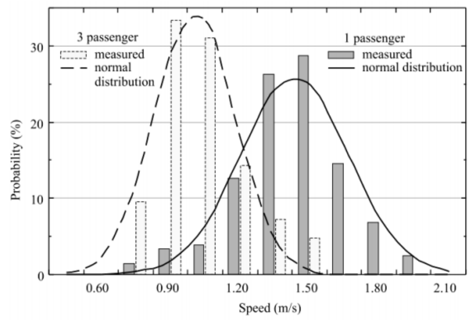

Figure 3: Group size interdependencies regarding to speed (Schultz, et al., 2010).

Figure 3 compares the differences in speed between groups with one and three members: groups with three members are clearly slower than groups that have onlyone member.

2.3. Effects of density on groups’ walking speed

The speed of pedestrians results clearly dependent on the density level. At low density, people walk faster than at higher density. This is in agreement with previous empirical and theoretical studies of pedestrian traffic (Seyfried et al. 2005).

Cepolina et al (2016) tried to find an empirical relationship between group speed and density from the data collected at the corridor at the Massachusetts Institute of Technology. For each density value, the average speed of the individuals that crossed the reference area in the given density conditions has been assessed and the resulting data are reported in figure 4 and figure 5. In figure 4, the points that refer to pedestrian walking alone have been marked with a diamond symbol whilst the points that refer to pedestrians walking in social groups have been marked with a star symbol.

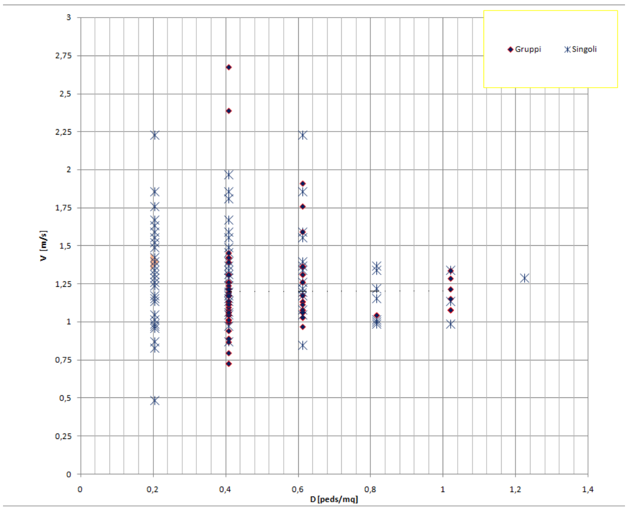

Figure 4: Pedestrian speed against density (Cepolina et al., 2016).

Figure 4 shows a large pedestrian speed variation, for each density value, for pedestrians walking alone; it is smaller for group members. According with previous studies, the speed of pedestrians walking in social group tends to be lower than speed of pedestrians walking alone at same level of density.

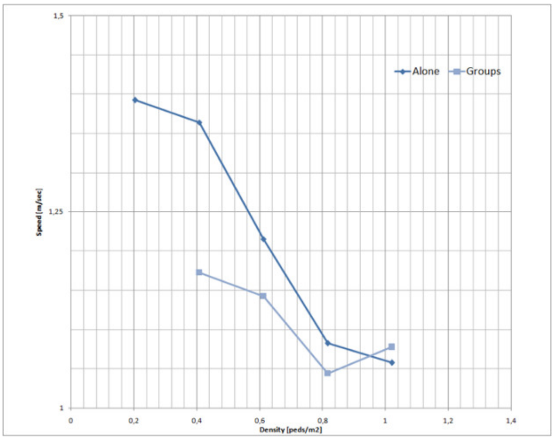

Figure 5: Average speed Vs. density for individual pedestrian and pedestrians in social groups (Cepolina et al. 2016)

Further, as shown in figure 5, the speed of pedestrians walking alone decreases faster than the one of pedestrians walking in groups as density increases. This fact makes explicit that some people walking in social groups are aware of the speed adjustments they have to cope with in order to keep walking in a group in medium density conditions.

2.4. Spatial organization of walking pedestrian social groups

Moussaïd, et al. (2010) investigated the spatial organization of walking pedestrian groups in two different population densities by analyzing the average angle and distance between group members. It has been suggested that at low density, people in the same group walk in a horizontal formation which enables them to communicate with other group members easily. While at moderate crowd density, this structure is hard to maintain without interfering with pedestrians outside the group. Therefore, the linear group structure will bend in the middle and form a 'V'-shaped formation. Moussaïd, et al. (2010) pointed out that this bending is forward in walking direction instead of backward, thus facilitates the social communication between group members (Figure 6 b). Though bending backward is a more flexible structure against the opposite pedestrian flow, it impedes the interaction within the group. Finally, at high density, the physical constraints would prevail over the social interaction, group members will walk behind each other and form a 'river-like' formation (Figure 6 c).

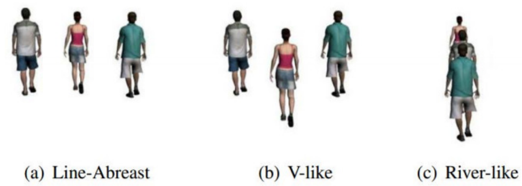

Figure 6: Group formations (Moussaid et al. 2010)

It is known that the distribution of spoken contributions among group members is not equal during a conversation: a few members speak most of the time, while the others listen (Stephan andMishler1952,Horvath 1965). Therefore, it is likely that pedestrians who talk more would end up in the middle of the group and the listeners would walk on the sides. In the same way, large groups would probably split up into subgroups around those who talk most.

2.5. Avoidance behavior of pedestrians that walk in groups

Singh, et al. (2009) filmed crowds in various locations around the University of Nottingham main campus and then analyzed the footage. The selected locations were chosen as they were long straight stretches of pathway, where it was possible to view people for a sufficient length of time to see their behavior after avoidance action had to be taken. Figure 7 shows the percentage of avoidance action taken when facing incoming pedestrians: 44% of the time, a person or subgroup will move to the right to avoid colliding with others and 34% of the time they will move to the left. The other 22% of the time, a subgroup will actually split to avoid colliding with people they are walking towards. The ratio of people moving to the left is higher than that of moving to the right:a possible explanation of this phenomenon is that the experiment was conducted in

UK, where left-hand traffic rule is applied (Cheng, 2014).

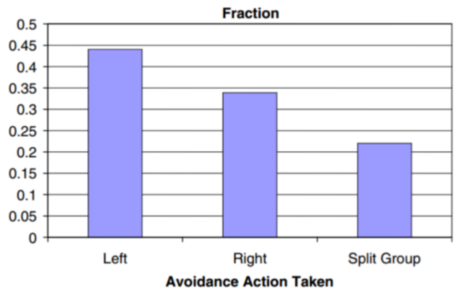

Figure 7: The avoidance action taken by people walking straight towards another (Singh et al., 2009).

The first observation by Singh, et al. (2009) is that a social group of people will usually avoid splitting if possible. This may mean that they will crowd closer together: rather than split up, the people in each social group move closer toward their companions and allow group members to enter their personal space. This therefore displays a preference of social groups to remain together.
Another finding is that an individual person is more likely to walk around a social group of people than walk through the middle of them. To avoid colliding with and splitting the group of two, an individual person not only moves aside but also steps onto a raised wall, highlighting the behavior described above.
When a social group does split, it is because there is an obstacle of something to avoid, usually another person or group. In the situation where there is more than one obstacle to avoid a social group will not regroup between them. Instead the group will remain apart and regroup only after all obstacles have been avoided.
Rastogi (Rastogi et al. 2011) observed that on sidewalks, pedestrians in large social groups (having 5 or more people) often split into smaller sub-groups in order to avoid incoming pedestrian flow. This splitting behavior decreases the group sizes, but increases the speed of pedestrian sub-groups. This phenomenon is absent on wide sidewalks and precincts because there is no restriction in space and large groups are not necessary to split into small sub-groups.

3. MICROSCOPIC MODELLING OF PEDESTRAIN SOCIAL GROUPS: DIFFERENT APPROACHES

According to Vizzari et al. (2013) we propose a schema classifying the different current approaches based on the way pedestrians are represented and managed. From this prospective, pedestrian models could be roughly classified into three main categories that respectively consider pedestrians as particles subject to forces, autonomous agents acting and interacting in the environmentor particular states of cells in which the environment is subdivided in Cellular Automata (CA) approaches

3.1. Particle based approach

Social force models are probably the most known method in the group of continuous models. Lewin and Cartwright (1952) suggested that the changes of human behaviorcan be guided by social forces or social fields. Based on this concept, Helbing and Molnár (1995) proposed the basic equation of the social force model to describe pedestrian motion:

$$\vec{F}_{\alpha}=\vec{F}^{0}_{\alpha}+\sum_{\beta}\vec{F}_{\alpha\beta}+\sum_{B}\vec{F}_{\alpha B}+\sum_{i}\vec{F}_{\alpha i} \qquad (1)$$

They assumed that a pedestrian's total motivation $\vec{F}_{\alpha}$ can belinearly influenced by three main factors:
(1) $\vec{F}^{0}_{\alpha}$ – the desire of pedestrian α to reach a certain destination or goal;
(2) $\sum_{\beta}\vec{F}_{\alpha\beta}$ – the total influence from other pedestrians β such as the repulsive effect of others;
(3) $\sum_{B}\vec{F}_{\alpha B}$ – the total repulsive force generated to avoid a border or an obstacle B.
In addition to the above four main effects, the social force model can be applied to demonstrate complex pedestrian behavior by adding a fluctuation term. This fluctuation term enables modelers to consider random variations of pedestrian behavior and make extension from the basic formula.
Using the social force model, several observed collective phenomena in pedestrian crowds have been successfully reproduced. This includes the lane forming behavior in crowds and the oscillatory walking pattern at a narrow exit (Helbing and Molnár1995) as well as the mechanisms in escape panic situations (Helbing et al. 2000).
In Moussaid et al.(2010) a new interaction term has been introduced in eq. 1:
(4) $\sum_{i}\vec{F}_{\alpha i}$ – the attraction of other persons or objects i: it describes the response to other group members.
Moussaid et al. (2010) postulate that the observed patterns of group organization result from the desire of their respective members to communicate with each other. Therefore, individuals continuously adjust their position to facilitate verbal exchange, while trying to avoid collisions with in-group members and out-group pedestrians.
The new interaction term has been assessed taking into account three facts: 1) group members turn their gazing direction to see their partners: the authors assume that the pedestrian adjusts its position to reduce the head rotation. 2) the pedestrian keeps a certain distance to the group's center of mass: according to observations, the average to the center of mass increases with group size. 3) there is a repulsion effect so that group members do not overlap each other.

Helbing, et al. (2005) conclude that the simplicity, linearity and small number of parameters are the main advantages of the social-force-based simulation. However, some researchers suggested that it is not easy to model heterogeneity and complex behaviors using social force model (Manenti et al. 2012).

3.2. Agent-based methods

The most common way to model the locomotion of human crowds is with agent-based methods, in which each agent plans individually its own actions. In agent based models, agents follow some pre-determined rules of behavior, which allow them to execute various behaviors appropriately in the modeled system.

In such approaches, global path planning and local collision avoidance are typically decoupled.

The agent perception model specifies the area which each pedestrian can perceive.Each agent has a set of behaviors, such as random movement, obstacle avoidance and maintaining group. Each of these behaviors is a steering behavior exited by some sensory inputs. Each agent individually perceives the situation according to its own characteristics, adapts its behavior according to the situation and chooses the nature of its interactions with the others.

Based on Reynolds's Open Steer environment (Reynolds1 999), Qiu and Hu (2010) proposed an agent-based simulation system for modeling crowd behavior with group structures, in which agents can move randomly, avoid obstacles and maintain group structures. The group movement is governed by the rule that each group is assumed to have a group leader and the leader would influence the decisions of other group members. However, in real-world situations, pedestrian groups are often composed of friends and families, where it is not necessary to have a group leader.

Agent based models are generally more computationally expensive than cellular automata and social force models, thus, modeling large systems is still a challenge for agent-based models

The agent basedapproach allows to include heterogeneity in pedestrian motion that improve simulation realism (Lemercier and Auberlet 2015). Heterogeneity could be performed by: turning the agents' external parameters values (such as speed, size, perception area) or implementing the ability for an agent to behave in different ways according his perception cognitive behavior.

Zhang et al. (2011) introduce heterogeneity in their simulation model by defining a level of communication for each agent that allows the flexible formation of small groups. Level of communication specifies the tendency of a member to talk with group members, and therefore maintain a closer spatial relationship. Intuitively, the group members with higher communicationability tend to keep closer for chatting. The member with highest communication would stay in the middle of the formation, with the others on both sides. Qiu and Hu (2010) proposed a model that allows to represent the heterogeneity nature of different groups and influences among group members. Two aspects have been introduced: intra-group structure and inter-group relationship. Intra-group structure refers to the network relationship among the members inside a group: different intra-group structures give rise to different shapes of a group. Inter-group relationship refers to the relationships among different groups: this is used to model the fact that groups also influence each other. However the model does not concern how the group structure is formed and how it will be dynamically changed.

A bilevel approach has been proposed by Karamouzas and Overmars (2012). Their model considerspairs and triples of characters and uses a two-step algorithm to ensure that the groups will stay as coherent as possible while avoiding collisions with other groups, individuals and static obstacles.

At every cycle of the simulation the desired velocity of each group is provided by some higher level path planning approach. Then, in the first step of the algorithm, an avoidance maneuver for each group of agents is determined. The authors formulate this as a discrete optimization problem of finding an optimal new formation and velocity for the entire group. In the second step of their approach, the computed solution velocity and formation are used to determine the desired velocity of each group member. This velocity is then given as an input to a local collision avoidance model which returns the new velocity for the group agent.

3.3. Cellula automata

A relatively novel model called Cellular Automata (CA) uses intuitive rules that make the model easy to understand without complex mathematical equations and thus demand less computation than social force models and agent based models. In cellular automata models, space is represented by a uniform grid of cells. At each discrete time step, the values of variables in each cell are updated according to a set of local rules and the values of variables in the cells at its neighborhood.

Cellular automata has been extensively used in modelling the crowd. In regular cellular automata models, each pedestrian occupies a single cell with the size of a pedestrian body. Since the space is divided into relatively large cells, the movements of pedestrians look like the movements of pieces on a chess board. Furthermore, all pedestrians have the same body size and speed. Pedestrian transition to neighboring cells is based on simple rules. Cellular automata transition rule could be simple mathematical equations which determine the next transition cell for each pedestrian. The next cell is normally one of the adjacent cells.

In Siamak et al. (2014), a method called "fine grid cellular automata"is proposed in which smaller cells are used and pedestrian body may occupy several cells. The model allows the use of different body sizes, shapes and speeds for pedestrian.

The majority of the pedestrian movements can be described in terms of movements toward successive targets. A least effort cellular automata model uses a measure distance to the target for calculating the probability of transition into neighboring cells.The concept of least effort (Zipf, 1949)mostly results into a shortest path straight line walking toward the target. In addition to least effort movement behavior, pedestrians show other behaviors like collision avoidance, density and congestion aversion and group formation. Siarmady et al. (2009) proposed a variation of least effort cellular automata algorithm which also considers the effect of pedestrian groups on crowd movement. The main idea behind the model is that pedestrians in a group maintain a short distance to the leader of the group or other group members.

The cellular automata models portray the interactions between pedestrians by intuitively understandable rule sets, rather than complex mathematical functions. It also provides an easier treatment of complex geometries than models with long-range interactions (Schadschneider, 2001). Therefore, one can easily implement cellular automata on computers and the computational speed is exceedingly fast compared to other microscopic pedestrian models. However, CA models have the disadvantage of dividing space into coarse cells, which may lead to larger errors than social force models in which space is not discretised (Köster et al. 2011).

Among the researchers who have used cellular automata for the simulation of pedestrian movements Dijkstra (Dijkstra, 2000), Blue and Adler (1998), Kirchner et al. (2001), Kirchner et al. (2003) and Schadschneider (2002) can be mentioned.

4. WEAKNESS OF THE CURRENT APPROACHES AND NEW POSSIBLE FUTURE DIRECTIONS

Planning and design of pedestrian environmentsis based on traffic efficiency that could be synthesized in the Level of Service, as it happens in the transport field.

The authors believe that the Level of Serviceshould be based on the individual perceived levels of service and not to average pedestrian flow characteristics. The individual perceived Level of Service should be related to the discomfort while walking in the pedestrian environment. The discomfort should be a function of: the personal space lost due to interactions with objects and other pedestrians and of reduced quality of the conversation and maybe,communication interruptions, in case of members of social groups. In assessing individual discomfort, heterogeneity in the pedestrian population is a key issue. A microscopic agent based approach seems suitable for this. As far as the authors know, no models have been developed for assessing discomfort at individual level. A first trial in this direction is the work performed by Cepolina et al. (Cepolina, Caroti et al.2015 and Cepolina, Cervia et al. 2015).

The overall traffic efficiency become relevant as density increases and become crucial in case of crowd accidents.

When density increases, crowd dynamics is characterized by spatial organization of group members, by segmentation of opposite flows in pedestrian counterstreams and by the zipper effect at bottlenecks. These emergent phenomena deeply affect the overall traffic efficiency (for instance in terms of pedestrian speed or walking times). Many of the reviewed microscopic simulators are able to give rise to these self organizing emergent phenomena and result suitable for testing the overall traffic efficiency of different pedestrian environment designs, in different density conditions.

In case of dense crowds and emergency situations, it has been demonstrated that communication between social group members do not take place but that other social and psychological factors significantly influence pedestrians' movements and, in case of crowd accidents, cooperative behaviors emerge. The dynamic of this temporal cooperation between pedestrians in crowds in emergent situations should be further studied and modeled:the reviewed models seem to not include it.

A robot that navigates in a pedestrian environment (as well as a video game player, or a person doing training, in a virtual environment) interacts with a population of pedestrians or avatars (in the second case).In these cases, heterogeneity in the behaviors of the pedestrians/avatars populationbecome crucial.Most current simulators animate homogeneous crowds. Some include underlying parameters that can be tuned to create variations within the crowd, others implement perception cognitive models and a few models use a personality model (Wiggins, 1996) as a basis for agent psychology. There is still considerable controversy in personality research over how many personality traits there are. Further research in agent psychology will increase the plausibility of virtual worlds and thus, improve robustness of robot navigation and of training activities.

The study of pedestrian social groups plays a very important role also in the case these groups include mobile robots as individuals and as a robot team. This may happen in next future in case of security problems or in case of natural risky events where robots and humans are required to efficiently cooperate.

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AUTHORS BIOGRAPHY

Elvezia M. Cepolina, PhD, assistant professorat the University of Pisa. She teaches Transport Planning at the UniversityofPisasince 2003. She has been research fellow at the University College London, UK.

Elveziahas been: coordinator of the FURBOT (Freight Urban RoBOTic vehicle) European project (FP7-SST-2011-RTD-1) and the person, for the University of Pisa, in charge of scientific and technical/technological aspects in the PICAV (Personal Intelligent City Accessible Vehicle System) European projects: (FP7-SST-2008-RTD-1).

Elvezia has been: Coordinator of the project "Analisi e simulazione del comportamento pedonale per una progettazione di ambient accessibili", PRA 2015 University of Pisa and International collaborator in the project "Pedestrian Simulation Contrasted with Reality", seed founded by the University of Pisa for

starting a research collaboration with Massachusetts Institute of Technology (USA)
Elvezia has been Overseas Scientist in the project SPIRAL Scientific Pedestrian Interaction Research in an Accessibility Laboratory, International Joint Project - 2004/R3-EU Europe (ESEP), founded by Royal Society, UK.
Elvezia is author of many papers on international journals and international conference proceedings.