Between Avoidance and Imitation: Plausible Wayfinding in Pedestrian Agent-Based Models

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***Abstract*—Extending the range of pedestrian decision making activities represented in a simulation model represents a serious challenge: different decisions are taken at distinct levels of abstraction, employing different types of information and knowledge about the environment, from path planning to the regulation of distance from other pedestrians and obstacles present in the environment. Pedestrians, moreover, are not robots: although empirical observations show that they consider congestion when planning, there are evidences that their decisions are not always optimal (even in normal situations). We present a model integrating and improving consolidated results mitigating the optimization effects of congestion aware path planning by making commonsense estimations of the effects of perceivable congestion, also embedding an imitation mechanism stimulating changes in planned decisions whenever another nearby pedestrian did the same. The model is formally described and experimented both in a validation scenario as well as in a real-world situation: an interesting counterintuitive result, in which reducing available choices and exits actually reduces overall egress time, is also presented and discussed.**

***Index Terms*—agent-based simulation, pedestrian simulation, wayfinding**

I. Introduction

Pedestrian and crowd simulation is a consolidated research and application context, in which results that lead to technology transfer (off-the-shelf available commercial tools are daily used by designers and planners) co-exist with open challenges for researchers in different fields and disciplines, to improve model expressiveness (i.e. simplifying the modeling activity or introducing the possibility of representing phenomena that were still not considered) and efficiency of the simulators based on those approaches. Trying to extend the range of pedestrian agents' decision making activities represented in a computational model represents a serious challenge, though: different types of decisions are taken at different levels of abstraction, employing different types of information and knowledge about the environment, from path planning (tactical level decision [1]) to the regulation of distance from other pedestrians and obstacles present in the environment (operational level decision). Moreover, the measure of success and validity of a model is definitely not the *optimality* with respect to some cost function, as (for instance) in robotics, but the *plausibility*, the adherence of the simulation results to data that can be acquired by means of observations or experiments.

In previous works we defined a model for the simulation of wayfinding decisions, especially considering the possibility of considering the perceivable congestion in agents' path planning [2]: the achieved results were somewhere between basic path planning exclusively based on a "shortest path" heuristics and a globally optimal solution. Later results [3] allowed us to further enrich the model, on one hand to embed an imitation mechanism for which a change in the initially planned line of action can be perceived by nearby agents and it can trigger analogous decisions. On the other, it supported a calibration of the significance of the different components of the wayfinding model, that are path length, perceived congestion and perceivable recent changes in the intentions of nearby pedestrians. In the present paper we improve and extend the above work by providing a deeper discussion and a more thorough evaluation of the implications of the commonsense evaluation of the effects of perceivable congestion on path planning and evaluating the effects of these modeling choices in a real-world scenario. New results show that the present model represents a step in the direction of a more plausible, although farther from optimality, overall simulation results.

The following Section will better set this work in the relevant literature, while Section III will formally describe the proposed modeling approach, that essentially incorporates an extension of the floor field [4] pedestrian modeling approach in which agents are provided with a representation of the environment in which they are situated, that they can employ to construct plans of action considering the above mentioned factors. Results of the model are provided in the form of calibration tests, provided in Section IV, and exploration of implications of the chosen path planning model in a real-world scenario, in Section V. Conclusions and future developments will end the paper.

II. Literature Review

The modeling of pedestrians' wayfinding decisions, especially considering the inevitable and empirically observed trade off between trajectory length and estimated travel time (considering the perceived congestion in alternative choices), represent an open challenge for pedestrian simulation research. Despite the topic has been considered by different disciplines studying spatial cognition processes for a long time, as testified by [5], research trying to provide empirical evidences supporting modeling and simulation efforts is still lively: for instance, [6] used a questionnaire to ask pedestrians what are the most relevant factor influencing their choices, whereas [7] actually performed both a simplified walking experiment involving wayfinding and also asked the involved participants to draw a trajectory on a map, in an outdoor setting; [8] describes observed trajectories followed by pedestrians attending a festival; [3] performed an experiment to observe actual wayfinding choices in a very simple situation, in which pedestrians had to choose between a short but congested path and a longer but faster one. All of these works show that wayfinding decisions are not exclusively determined by the length of the path or the expected travel time, and they highlight that pedestrians actually do not choose optimal paths even in normal, non stressful situations. Despite these results, however, the support to the modeling of this kind of decision making activities is still in relatively early stages.

Most works in the area of pedestrian and crowd simulation investigate wayfinding from the perspective of including in the model the necessary elements to perform the wayfinding operation from the first execution of the model. The approach described in the previously mentioned work by [8] considers spatial cognition aspects, in particular combining allocentric and egocentric contributions to overall pedestrian navigation in an integrative approach considering different heuristics. Results of the approach have been proposed showing a good accordance with empirical observations in outdoor situations, the kind of scenario in which the approach seems more plausible. [9] explored the implications of different strategies for the management of route choice operations, through the combination of applying the shortest or quickest path, with local (i.e., minimize time to vacate the room) or global (i.e., minimize overall travel time) strategies. [10] proposed the modification of the floor-field Cellular Automata [4] approach for enabling pedestrian choices also considering the impact of congestion on the expected travel time in evacuation situations. [11] proposed a pedestrian model to simulate route choice in case of evacuation and they were able to reproduce the observed data of an experiment. [12] also considered evacuation situations, discussing the results of an experiment about the evacuation of a classroom with two exits, proposing a cellular automata model, whereas [13] studied the evacuation of a two exits classroom, proposing a differentiation between *rational* behavior, mainly aimed at optimizing the own travel time, and *irrational* one, attracted by the choices of other people and leading to higher evacuation times. Although the results of the above cited works are an interesting starting point for further studies, they are not conclusive.

It is important to highlight that all of the above cited approaches imply that modeled pedestrians are provided with a complete map of the environment in which they are situated. Whereas this seems a rather implausible assumption, we must consider that these research efforts are generally set within or very close to the transportation research area: within a train station, it is almost inevitable to find first time visitors of such an environment, nonetheless their presence represents generally a small minority of the simulated population and they are often not considered to evaluate the performance of the design in withstanding a certain type of demand.

III. Simulating Walking and Route choice of Pedestrians

A. *The Representation of the Environment and the Knowledge of Agents*

The adopted agent environment [14] is discrete and modeled with a grid of 40 cm sided square cells: the size considers the average area occupied by a pedestrian [15], and it allows representing reasonable densities usually observed in real scenarios. The cells have a state informing nearby agents about their movement possibilities: they can be vacant or occupied by an obstacle or at most two pedestrians, so as to be able to manage locally high density situations [16]. This modification to the basic floor field approach is based on observations described by [17] that highlight the fact that in some situations (especially counter-flows) pedestrians actually adjust their spatial orientation to temporarily accept a reduction of their personal space to allow a smoother flow.

To allow the configuration of a pedestrian simulation scenario, several *markers* are defined with different purposes in addition to the basic map of the area describing obstacles and walkable space. This set of objects has been introduced to allow the movement at the operational level and the reasoning at the tactical level, identifying intermediate and final targets for agents' plans: (i) *start areas*, generating agents in the simulation; (ii) *openings*, sets of cells that (together with obstacles) divide the environment into regions; (iii) *final destinations* of agents, generally implying their removal from the simulation.

An example of environment annotated with this set of markers is proposed in Fig. 1(b): the above model implies the fact that the environment is divided in *regions* that, as well as other markers, are associated to additional relevant metadata used to characterize the associated element (e.g. define the demand associated to a start area).

This model uses an extended version of the *floor fields* approach [4] for supporting agents' navigation at locomotion/operational level, using the agents' environment as a container of information for the management of the interactions between entities. In this particular model, discrete potentials are spread from cells of obstacles and destinations, informing about distances to these objects. The two types of floor fields are denoted as *path field*, spread from openings and final destinations (one per destination object), and *obstacle field*, a unique field spread from all the cells marked as obstacle. In addition, a *dynamic* floor field that has been denoted as *proxemic field* is used to reproduce a proxemic behavior [18] in a repulsive sense, allowing agents to preserve acceptable distances from other agents. The overall approach generates a plausible navigation of the environment as well as an anthropologically founded means of regulating interpersonal distances among pedestrians.

This framework, on one hand, enables the agents to have a position in the discrete environment and to perform movement towards a user configured final destination. On the other hand,

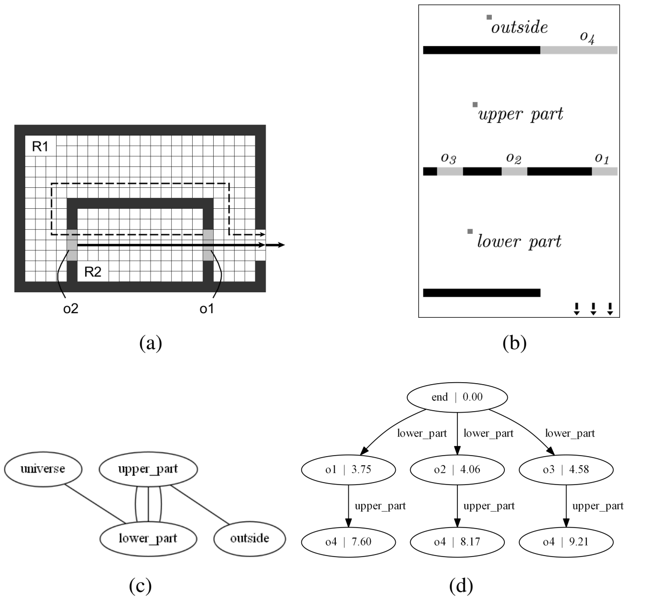


Fig. 1. (a) An example of plausible (continuous line) and implausible (dashed) paths in a simple environment. (b) An experimental scenario (two open areas connected by means of a constrained corridor separated in two sections connected by three openings - o_1, o_2, and o_3,) with the considered annotation tools and its respective cognitive map (c) and the shortest path tree leading to the southern exit (d).

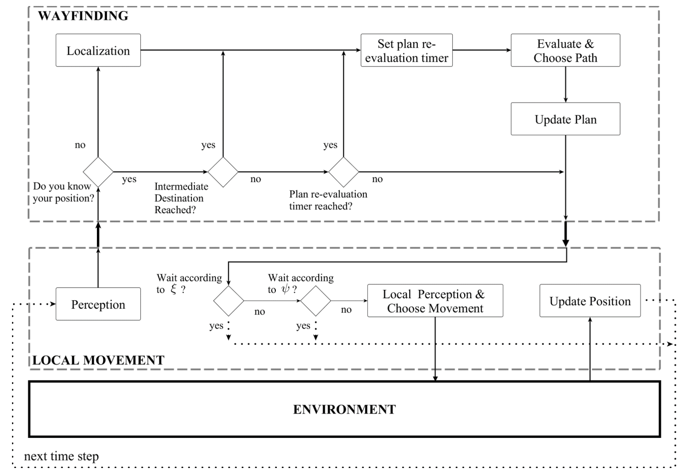


Fig. 2. The complete life-cycle of the agent.

the presence of intermediate targets supports choices at the tactical level of the agent, with the computation of a graph-like representation of the walkable space, based on the concept of *cognitive map* [19]. The method for the computation of this environment abstraction has been defined in [20] and it uses the information of the scenario configuration, together with the floor fields associated to openings and final destinations. In this way a data structure for a complete knowledge of the environment is pre-computed. The cognitive map identifies *regions* (e.g. a room) as nodes of the labeled graph and *openings* as edges. An example of the data structure associated to the sample scenario is illustrated in Fig. 1(c). Overall the cognitive map allows the agents to identify their position in the environment and it constitutes a basis for the generation of an additional knowledge base, which will enable the reasoning for the route calculation.

This additional data structure has been called *Paths Tree* and it contains the information about *plausible* paths towards a final destination, starting from each region of the environment. The concept of plausibility of a path is encoded in the algorithm for the computation of the tree, which is discussed in [2] and only briefly described here. The procedure starts by considering the destination as the root of a tree that is recursively expanded, adding child nodes mapped to an intermediate destination reachable in the region. Nodes are added if the constraints describing the plausibility of a path are satisfied: in particular, paths that imply cycles or a not reasonable usage of the space (e.g. passing inside a room to reach the exit of a corridor, as illustrated in Fig. 1(a)) are simply avoided.

The results of the computation is a tree whose nodes are mapped to targets in the environment and each edge refers to a particular path between two targets. The root of the tree is a final destination, while the underlying nodes are only mapped to openings connected or reachable from it. To complete the information, each node n is labeled with the free flow expected travel time (i.e. without encountering any congestion in the path) associated to the path starting from the center of the opening associated to n and passing through the center of all openings mapped by the parent nodes of n, until the final destination.

For the choice of their path, agents access the information of a Paths Tree generated from a final destination End with the function $Paths(R, End)$. Given the region R of the agent, the function returns a set of couples $\{(P_i, tt_i)\}$. $P_i = \{\Omega_k, \ldots, End\}$ is the ordered set describing paths which start from Ω_k, belonging to $Openings(R)$, and lead to End. tt_i is the associated free flow travel time.

B. The Route Choice Model of Agents

This aspect of the model is inspired by previously discussed empirical evidences suggesting the following stylized facts about pedestrian tactical level decisions: (i) they are able to consider perceivable congestion when planning their paths; (ii) their reasoning is inevitably imprecise, both due to the limited time spent for the decision as well as to the imprecise estimates results of individual perception; (iii) they are influenced by nearby pedestrians also through imitation mechanisms, apparently conflicting with the general avoidance tendency.

By considering these aspects, the proposed approach enables agents to choose their path considering distances as well as the evolution of the overall simulation dynamics, especially considering visible changes in decisions of preceding agents. At the same time, the model must provide a sufficient variability of the results (i.e. of the paths choices) and the possibility to be calibrated to reflect observed empirical data.

The workflow of the agent is again reported in Figure 2, to allow the understanding of the tasks related to route choice.

First of all, the agent performs a perception of its surrounding situation, considering its knowledge of the environment, aimed at understanding its position and the markers perceivable from its region (e.g. intermediate targets). At the very beginning of its life, the agent does not have any information about its location, thus the first assignment to execute is a *self localization*: it basically implies to perceive the values of floor fields in its physical position and infers the location in the Cognitive Map. Once the agent is aware of the region where it is situated, it loads the Paths Tree and evaluates the alternatives leading to its final destination.

Figure 2 also emphasizes that the evaluation of the possible paths and the re-consideration of the plan do not only occur when the agent is created in the simulation or when it passes from a region to another (i.e. when new elements influencing the choice can be perceived). The evaluation is also performed at specific intervals, according to a timer that can assume two possible values: (i) a value defining a short interval, set right after the agent performs a *change* of its current plan, to evaluate its adequacy (the new plan, in fact, could lead to acquire new information about the state of the environment potentially indicating that the new path leads to a worst congestion than the one avoided); as a result of the evaluation associated to the short interval timer, (ii) a higher value is set when the agent confirms the current choice of path, or if it changes back to the previous choice employed after the short interval. This timer-based mechanism is introduced to limit the natural non-determinism of the probabilistic approach employed in this model and to avoid excessively frequent changes in the adopted plan.

The evaluation of a potential plan is designed through the concept of *path utility*, assigned to each alternative: just like for the selection of the next cell at operational level, also the choice of the overall plan of actions (i.e. set of intermediate markers leading from the current region to the desired exit) is in fact based on a probabilistic decision. The result of this process generates a new intermediate target of the agent, used to update the reference to the floor field to be followed at the operational layer.

1) The Utility and Choice of Paths: The function that defines the probability of choosing a path is exponential with respect to the utility value associated to it. This is essentially analogous to the choice of movement at the operational layer: $Prob(P) = N \cdot e^{U(P)}$

The usage of the exponential function for the computation of the probability of adopting a path P is a good solution to emphasize the differences in the perceived utility values of paths, limiting the choice of relatively bad solutions, such as those associated to much longer paths. More precisely, $U(P)$ comprises the three observed components influencing the route choice decision, which are aggregated with a weighted sum:

$$U(P) = \kappa_{tt} Eval_{tt}(P) - \kappa_q Eval_q(P) + \kappa_f Eval_f(P) \quad (1)$$

where the first element evaluates the *expected travel times*; the second provides a commonsense evaluation of the *queuing* (crowding) conditions through the considered path and the last one introduces a positive influence of perceived choices of nearby agents to pursue the associated path P (i.e. imitation of emerging leaders). All the three functions provide values normalized within the range $[0, 1]$, thus the value of $U(P)$ is included in the range $[-\kappa_q, \kappa_{tt} + \kappa_f]$.

2) The Evaluation of Traveling Times: The evaluation of traveling times is a crucial element of the model: even if it is not the only considered factor, it still represents an extremely significant element for routing decisions. First of all, the information about the travel time tt_i of a path P_i is derived from the relevant Paths Tree. In particular, $Paths(R, End)$ is used, where End is the agent's final destination (used to select the appropriate Paths Tree), and R is the region in which the agent is situated (it is used to select the relevant path P_i in the Paths Tree structure). This information is integrated with the free flow travel time to reach the first opening Ω_k described by each path:

$$TravelTime(P_i) = tt_i + \frac{PF_{\Omega_k}(x, y)}{Speed_d} \quad (2)$$

where $PF_{\Omega_k}(x, y)$ is the value of the path field associated to Ω_k in the position (x, y) of the agent and $Speed_d$ is the *desired velocity* of the agent, that can be an arbitrary value. The value of the traveling time is then evaluated by means of the following function:

$$Eval_{tt}(P) = N_{tt} \cdot \frac{\min\limits_{P_i \in Paths(r)} (TravelTime(P_i))}{TravelTime(P)} \quad (3)$$

where N_{tt} is the normalization factor, i.e., 1 over the sum of $TravelTime(P)$ for all paths. By using the minimum value of the list of possible paths leading the agent towards its own destination from the current region, the range of the function is set to (0,1], being 1 for the path with minimum travel time and decreasing as the difference with the other paths increases. This modeling choice, makes this function describe the *utility* of the route in terms of travel times, instead of its *cost*, but the most important consideration is that it allows performing a normalization employing the minimum travel time instead of the maximum. This improves the robustness of the function with respect to the presence of outliers, few paths (even just one) characterized by very high travel times that would essentially flatten the differences among cost values of other reasonable choices after the normalization, reducing its discriminating power.

3) The Evaluation of Congestion: The behavior modeled in the agent in this model considers congestion as a negative element for the evaluation of the path. However, by acting on the calibration of the parameter κ_q it is possible to define different classes of agents with customized (and potentially dynamic) behaviors, also considering attraction to congested paths with the configuration of a negative value to generate mere following or herding behaviors.

For the evaluation of this component of the route decision making activity associated to a path P, a function is first introduced for denoting agents that precede the evaluating agent a in the route towards the opening Ω of a path P:

$$\begin{aligned} &Forward(\Omega, a) = \\ &\qquad |\{a' \in Ag \backslash \{a\} : Dest(a') = \Omega \wedge \\ &\qquad PF_{\Omega}(Pos(a')) < PF_{\Omega}(Pos(a))\}| \end{aligned} \tag{4}$$

where Pos and $Dest$ indicate respectively the position and current destination of the agent; the fact that $PF_{\Omega}(Pos(a')) < PF_{\Omega}(Pos(a))$ assures that a' is closer to Ω than a, due to the nature of floor fields. Each agent is therefore able to perceive the main direction of the others (its current destination). This kind of perception is plausible considering that only preceding agents are counted, but we want to restrict its application when agents are sufficiently close to the next passage (i.e. they perceive as important the choice of continuing to pursue that path or change it). A schema providing a sample situation describing the above defined functions is shown in Figure 3 (a): in particular, agent A_1 has five other agents that should reach passage Ω_1 before it, according to current intentions and state of the environment (agent A_2 is actually farther from Ω_1), whereas there are six other agents that should arrive to Ω_2 before it, should it change its plan (something that seems implausible given this state of the system). To introduce a way to calibrate this perception, the following function and an additional parameter γ are introduced:

$$PerceiveForward(\Omega, a) = \begin{cases} Forward(\Omega, a), & \text{if } PF_{\Omega}(Pos(a)) < \gamma \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

The function $Eval_q$ is finally defined with the normalization of values of $PerceiveForward$ for all the openings connecting the region of the agent:

$$Eval_q(P) = N \cdot \frac{PerceiveForward(FirstEl(P), myself)}{width(FirstEl(P))} \tag{6}$$

where $FirstEl$ returns the first opening of a path, $myself$ denotes the evaluating agent and $width$ scales the evaluation over the width of the door (larger doors sustain higher flows). It must be emphasized that this modeling choice represents a deliberately imprecise estimation of the expected increase in the travel time towards the next intermediate goal, a form of commonsense reasoning, in the vein of [21], unlike what happens in a previous modeling effort [2].

4) Propagation of Choices - Following Behavior: This component of the decision making model aims at representing the effect of an additional stimulus perceived by the agents associated to sudden decision changes of other persons that might have an influence. An additional grid has been introduced to model this kind of event, whose functioning is similar to the one of a dynamic floor field. The grid, called *ChoiceField*, is used to spread a gradient from the positions of agents that, at a given time-step, change their plan due to the perception of congestion.

The functioning of this field is described by two parameters ρ_c and τ_c, which defines the diffusion radius and the time

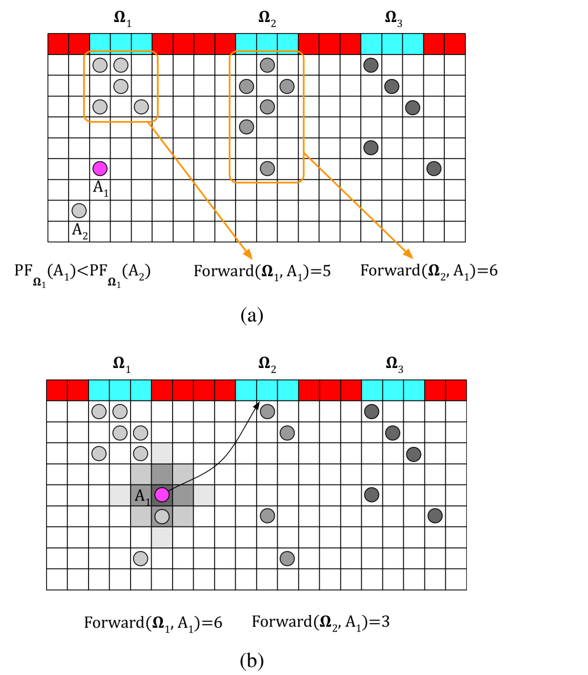


Fig. 3. Example situations describing $Forward$ function (a) and $ChoiceField$ (in particular, for $\rho_c = 3$) (b).

needed by the values to *decay*. The diffusion of values from an agent a, choosing a new target Ω', is performed in the cells c of the grid with $Dist(Pos(a), c) \leq \rho_c$ with the following function:

$$Diffuse(c, a) = \begin{cases} 1/Dist(Pos(a), c) & \text{if } Pos(a) \neq c \\ 1 & \text{otherwise} \end{cases} \tag{7}$$

The diffused values persist in the *ChoiceField* grid for τ_c simulation steps, then they are simply discarded. The index of the target Ω' is stored together with the diffusion values, thus the grid contains in each cell a vector of couples $\{(\Omega_m, diff_{\Omega_m}), \ldots, (\Omega_n, diff_{\Omega_n})\}$, describing the values of influence associated to each opening of the region where the cell is situated. While multiple neighbor agents changes their choices towards the opening Ω', the values of the diffusion are summed up in the respective $diff_{\Omega'}$. In addition, after having changed its decision, an agent spreads the gradient in the grid for a configurable amount of time steps represented by an additional parameter τ_a. In this way it influences the choices of its neighbors for a certain amount of time. Figure 3 (b) shows a sample situation in which agent A_1, as a consequence of changing its next intermediate target from Ω_1 to Ω_2, spreads a *ChoiceField* (with range $\rho_c = 3$) that can be perceived by the agent immediately following it.

The existence of values $diff_{\Omega_k} > 0$ for some opening Ω_k implies that the agent is influenced in the evaluation phase by one of these openings, but the probability for which this influence is effective is, after all, regulated by the utility weight κ_f. In case of having multiple $diff_{\Omega_k} > 0$ in the same cell, a individual influence is chosen with a simple probability function based on the normalized weights $diff$ associated to the cell. Hence, for an evaluation performed by an agent a at time-step t, the utility component $Eval_f$ can be equal to 1 only for one path $\overline{P}$, between the paths having $diff_{\Omega_k} > 0$ in the position of a.

IV. Validation of the model

While operational level aspects of pedestrian modeling and simulation have a reasonably stable set of results that a plausible simulation model should produce (to the point that there is even a technical note by the National Institute of Standards and Technology on this point [22]), a similar type of standard validation process for tactical level decisions and wayfinding is still not feasible due to lack of knowledge and data. For these reasons, an experiment involving human participants in a controlled setting has been performed in 2015 and its results have inspired and have been used for the design, calibration and initial validation of the wayfinding model.

The experiment has been configured to achieve evidences regarding the influence of crowding conditions on the route choice. 46 students participated to the experiment, and the setting was designed to describe an elementary choice: it was characterized by a rectangular environment divided in two areas of equal size along the long side, each one of 7.2×6 m^2. The two sides were connected by three passages, which were creating three paths of different lengths, respectively Path$_a$, Path$_b$ and Path$_c$ in order of length: Figure 1(b) graphically describes this scenario. The two gates defining longer routes were closed according to four different procedures: (1) only the shortest path was available; (2) Path$_a$ and Path$_b$ open; (3) Path$_a$ and Path$_c$ open; (4) all paths available. Each procedure has been repeated four times to achieve more consistent data. For each procedure, the number of people employing each path has been manually counted. More thorough details about the experiment can be found in [3].

A similar setting has been simulated with the three simulation case studies: (i) wayfinding based on shortest path; (ii) wayfinding based on quickest path, as defined in [2]; (iii) wayfinding with the proposed model. Results are reported in Table I. To achieve consistent and reliable results, a set of 50 simulations has been performed for the bottleneck scenario, for each width of the door. A smaller set containing longer runs has been configured for the fundamental diagram tests, where the corridor was configured as toroidal with respect to the long side in order to maintain the same global density. The chosen configuration $(\kappa_{tt}, \kappa_q, \kappa_f) = (100, 25, 5)$ of the parameters is effective to reproduce the distribution of chosen paths over the simulated pedestrians, leading to much closer results to the empirical data than with the other two case studies.

V. Simulation of a Realistic Scenario

This section shows the application of the proposed and overall model in a realistic scenario, simulating a sample egress from a football arena similar to the one described by [9]. The aims are: (i) to allow the reader to understand the impact of the chosen modeling purposes on the simulated dynamics; (ii) to discuss the difference of the results proposed by the current model with a baseline implementation based on a pure floor-field approach and with the model proposed in [2], which describes a model of wayfinding considering in a more analytically precise the effects on the perceivable level of congestion, without considering imitative effects. Finally, a simple modification of the analyzed spatial configuration is evaluated with additional simulations, identifying how counterintuitive results – similar to well-known paradoxes in the transportation field [23], and also present in pedestrian dynamics [24] – can be observed in this particular scenario.

Procedure 2	**Path$_a$**	**Path$_b$**	**Path$_c$**
Experiment	23.2	22.8	0
wayfinding based on shortest path	30.1	14.9	0
wayfinding based on [2]	40.8	5.2	0
Present model	23.9	22.1	0
Procedure 3	**Path$_a$**	**Path$_b$**	**Path$_c$**
Experiment	28	0	18
wayfinding based on shortest path	46	0	0
wayfinding based on [2]	44.9	0	1.1
Present model	28.6	0	17.4
Procedure 4	**Path$_a$**	**Path$_b$**	**Path$_c$**
Experiment	20.8	18	7.2
wayfinding based on shortest path	30.1	14.9	0
wayfinding based on [2]	40.8	5.2	0
Present model	19.3	17.8	8.9

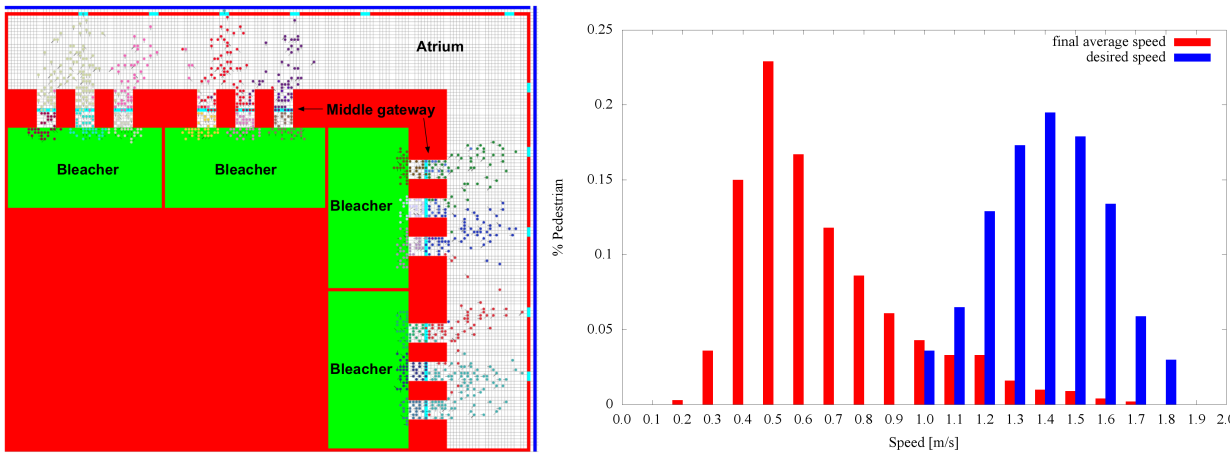
TABLE I
AVERAGE CHOSEN PATHS (OBSERVED AND SIMULATED) OF PEDESTRIANS IN THE EXPERIMENTAL SCENARIO DESCRIBED IN [3].

Decision Parameters	**Value**
utility parameter κ_{tt}	100.0
utility parameter κ_q	25.0
utility parameter κ_f	5
***ChoiceField* Parameters**	
diffusion radius parameter ρ_c	1.2 m
decay parameter τ_c	0.5 s
diffusion time of agent τ_a	1 s

TABLE II
CALIBRATION PARAMETERS USED FOR THE WAYFINDING MODEL.

The scenario is represented in Fig. 4(a): 4 starting areas (green in the figure) are associated to the bleachers of the stadium and they generate the agents in the simulation, whose aim is to reach the outside area indicated with the blue object (i.e. the Northern and Eastern borders of the scenario). Cyan objects are the intermediate targets, generating the alternative opportunities for agents' wayfinding decisions. Larger ones and closer to the start areas represents the corridors connecting the bleachers to the atrium, where a total of 11 doors of 1.2 m of width provide the way out from the stadium. 250 agents are generated in random positions of the related start area at the beginning of the simulation, producing a total of 1000 pedestrians. The parameters of the model are the same one employed for the validation tests.

Differences among pedestrians are introduced with respect to the desired walking speed, defined through a discretization of a Gaussian distribution described by $\mu = 1.4$ m/s and $\sigma = 0.2$ m/s, to represent an egress situation in normal conditions. The maximum speed in the model is set to 1.8 m/s to cover the majority of values defined by the distribution. An example distribution from one simulation run is shown in Figure 4(b). The structure of the environment and the nature of the simulated situation limit the impact of the assumption that



(a) (b)

Fig. 4. (a) A screenshot from a simulation run describing the environment used for the experiments. Colors of objects define their type as explained in Section III, while the color of the agents informs about their current target. (b) Configured distribution of desired speeds (blue) and final average speeds (blue) of agents. Both images refer to one simulation run of the 3^{rd} case study.

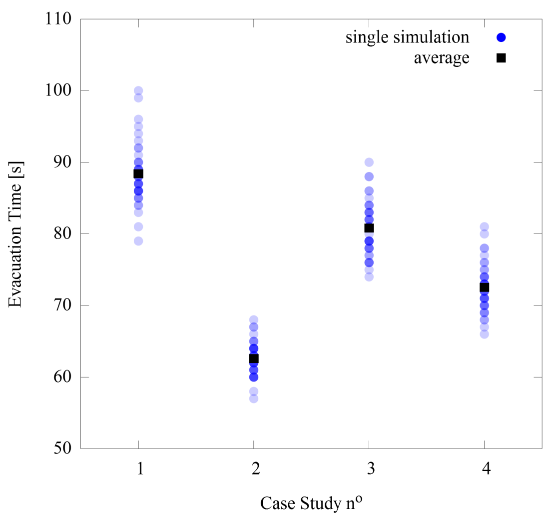


Fig. 5. Comparison of evacuation times of the whole environment achieved among the 4 scenarios. The black square represents the average, while the individual time related to one iteration is plotted with a transparency effect to describe the distribution.

agents are provided with a complete map of the environment: first of all, pedestrians are in the process of exiting from the environment, which means that they have already seen a portion of the area at least once; moreover, the map is quite simple, with associated plans that require the passage between just one intermediate target (i.e. the associated path trees are surely wide but quite shallow).

Within the illustrated scenario, four case studies have been simulated with sets of 50 simulation runs, a number sufficient to achieve consistent results. Case Study N. 1 aims only at achieving a base line dataset, describing the results achievable by only using the model at the locomotion layer following the "shortest path" heuristics, without a dynamic wayfinding: the fact that most direct gateways are used by a large number of pedestrians causes congestions that are apparent in space utilization diagrams that will be described later on, and that also have an influence on the total evacuation time. Case Study N. 2 represents uses the wayfinding model proposed in [2] that essentially tries to select the *quickest path*, employing an analytically precise estimation of the impact of perceived congestion surrounding the nearest intermediate targets (that are supposed to be perceivable from the regions of which they represent a border). Agents are therefore able to select the best alternative at the time of planning to the shortest path in case of a congested environment. Case Studies N. 3 and 4 use the model described in this paper, with parameters set to $\kappa_{tt} = 100,\ \kappa_q = 25,\ \kappa_f = 5$. The fourth scenario is configured with a modified version of the environment, achieved by actually closing the middle gateway connecting the bleachers to the atrium: this represents a counterintuitive design choice, since it makes more difficult to exit the bleachers area but, on the other hand, the atrium turns out to be much less congested, smoothening the flow towards the final exits, reducing the overall egress time.

These above discussed features are clarified with the results shown in Figure 5, and 6. In particular, Figure 5 shows the evacuation times of each run of the simulation sets of the case studies, simply calculated as the time interval starting at the beginning of the simulation and ending when the last agent reaches its final destination, vacating the area. The model described in [2] is substantially more efficient in terms of travel times of agents, achieving an average evacuation time of about 62 s. This is due to the effective strategy of the agents that leads to an extremely well balanced usage of the exit doors, shown in Figure 6(b): this kind of diagram shows the evacuation times over the space. The values shown in the map are achieved by storing the latest time step $\hat{\tau}$ in which each cell has been occupied by a pedestrian in the simulation, representing essentially how long it takes to vacate the area associated to a given cell. Adopting the quickest path approach the emptying times are extremely well balanced in the available exits, something that does not happen with the case study 3, where the two exit doors at the extremes of the scenario become the most used due to their attractiveness in terms of utility (they are the most obvious choices for the agents coming from the top left and bottom right start areas, due to the short distance). Some pedestrians initially directed towards those exits, actually change the initial plan and finally select other nearby and less congested exits, but this does not happen so systematically as for case study 2.

Finally, case study 4 represents a typical "what–if" scenario: in fact, we considered the issue of congestion in the exits from the atrium and tried to actually reduce the flow from the bleachers area by deciding not to use the central of the three gateways from those areas to the common atrium. While this certainly increases the congestion in the remaining passages (although the maximum measured level of density is lower than the one achieved in case study 3), the overall evacuation time is significantly lower and the density in the atrium is also much lower.

An additional, although less perceivable, effect of the adoption of the model proposed in this paper is the fact that available exits that are far from the gateways connecting the bleachers and the atrium, which are actually never used in case study 1 and extremely rarely employed in case study 2, are slightly more frequently selected in case studies 3 and especially 4. Considering overall evacuation time, the approach adopted in case study 2, that is the algorithm proposed in [2], actually represents a very rational choice from the collective intelligence perspective, and it produces results that are likely close to the system optimum (surely closer than all the other proposed alternatives). This is particularly evident by looking at Figure 6(b), where the emptying times are balanced among the exit doors, much differently from what shown by Figure 6(c). This difference actually represented one of the main motivations leading to the definition of the model here proposed. Indeed, several works from the literature (e.g. [25]) generally observe an unbalanced usage of exit doors in evacuation drills, leading to evacuation times even significantly higher then in the optimal case. Moreover, the fact that this model is calibrated employing results of an experimental observation supports the conjecture that it represents an approach closer to the actual wayfinding strategies employed by pedestrians in everyday situations.

VI. Conclusions and Future Works

The paper has presented an approach integrating and improving consolidated results on the modeling of pedestrian behavior at the basic locomotion level with higher level decisions on the overall path to be followed in an environment composed of several regions connected by different gateways or passages. The model, derived as an extension of a previous approach described in [2], has been set in the relevant literature and it has been formally described, motivating its components, calibrating it on an observed situation, showing exploratory results in a real-world situation, in which the implications of its application are discussed in comparison with results of existing approaches from the literature. In particular, thanks to the empirical results and calibration performed in [3], we consider the present results as a step in the direction of more plausible wayfinding decisions, that are surely more effective than baseline "shortest path" based heuristics, but not as close to optimality as results of a previous approach [2].

Current and future works are aimed at incorporating results on the impact of groups in the simulated pedestrian population within the wayfinding decisions; we are also considering the opportunity of developing a serious game, also employing video games and virtual reality technologies, to achieve a more sustainable way of acquiring empirical evidences on human wayfinding. This would allow to consider arbitrary environmental structures, also more complicated than the ones studied and simulated so far, and to achieve a more thorough validation of the proposed model.

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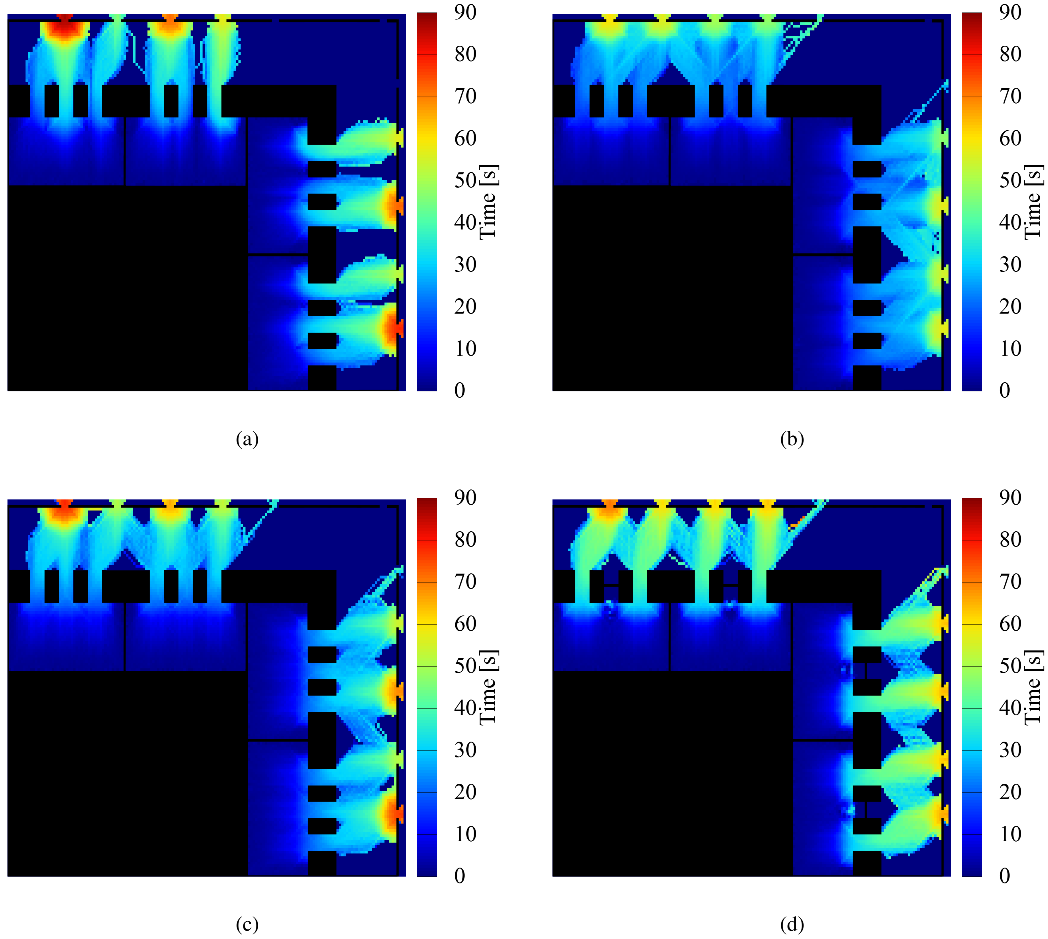

Fig. 6. Evacuation times over the space in the simulated case studies, averaged over the 50 iterations.

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