Using a multi-scale model for simulating pedestrian behavior

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Abstract. In order to model realistic pedestrian crowds, different aspects on different scales have to be taken into account. Besides behavioral aspects, locomotion on short-scale and human navigation on large-scale have to modeled appropriately. In the simulation models existing to date, these two aspects are modeled separately. To overcome the limitations of currently available models, this paper presents a new hybrid multi-scale model, which closely links information between the short-scale and the large-scale layer to improve the navigational behavior.
In the presented hybrid navigation model, graph-based methods using visibility graphs are used to model large-scale way-finding decisions. The pedestrians' movements between two nodes of the navigation graph (the short-scale) are modeled by means of a dynamic navigation floor field. The floor field is updated dynamically during the runtime of the simulation, explicitly considering other pedestrians for determining the fastest path.

Keywords: wayfinding, navigation, dynamic navigation fields, dynamic floor fields, cellular automata, visibility graphs, locomotion, route choice, multi-scale model, microscopic pedestrian simulation

1 Introduction

Simulation of crowd dynamics has become an important field of research in the last years. A variety of different approaches have been developed, focusing on different objectives. Microscopic multi-scale models form one type of models (e.g. [1], [2], [3]). These approaches model crowd behavior on different scales: on the small scale, locomotion is modeled, i.e. how do pedestrians move (stroll, walk, run) towards a visible destination while trying to avoid other pedestrians. These aspects are mostly modeled either by cellular automata combined with force models or with continuous floor fields. Each individual's step is calculated according to given potentials (i.e. gradients of the potentials) or forces, until all individuals have reached a designated destination. On the large-scale, navigational aspects are addressed. These include the route choice towards a (not visible) destination via intermediate destinations. The decision of which way to take at each intermediate destination might depend on environmental conditions, e.g. choosing illuminated paths in the evening, and can vary from pedestrian to pedestrian, e.g. take the shortest path, take the fastest path, avoid congestions, follow signage, follow friends, etc. To model these aspects, graphs such

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as Voronoi diagrams (e.g. [4]), visibility graphs (e.g. [5]), or corridor maps [6] are used and different routing algorithms are applied on those.
Various models combine these scales into so-called multi-scale models, combining graph-based approaches either with force models (e.g. [3],[7],[8]) or with agent type models (e.g. [9]-[13],[31]). However, these multi-scale models typically combine the small-scale and large-scale layer in a very simplistic fashion. Thus the limitations of small scale (e.g. being short-sighted) and large scale (e.g. not considering other moving pedestrians for route choice decisions) are usually not resolved. Typically, the large-scale layer provides the next intermediate destination to pedestrians steering in the small-scale layer and no information sharing between the small-scale and the large-scale layer takes place.
In this work, a new hybrid multi-scale approach is proposed, in which a combination of the small-scale and the large-scale layer is driven further: we share information between both layers to improve the accuracy of the model resolving the above mentioned issues.

2 State of the Art

To date, the small-scale and the large-scale layer are combined as follows to form a multi-scale model: The navigation graph is used to generate pedestrians' paths based on a specific navigation strategy. Paths themselves consist of a list of intermediate destinations. The navigation field is then used to navigate pedestrians between these intermediate destinations until the final destination is reached. Although the combination of the layers already improves the realism of simulations, since small scale aspects (e.g. avoiding other moving pedestrians in close vicinity) and large-scale aspects (e.g. navigation strategy) are addressed, there are still several open issues to be solved:

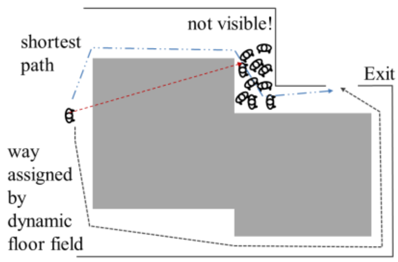

Fig. 1. Example for not distinguishing visible and invisible edges: The pedestrian on the left would walk around the south-west corner navigating according to a dynamic floor field, although he cannot see the congested area from his position

Current models are limited by the lack of information exchange between the layers resulting in unrealistic effects. On the small scale, static floor fields are often used [14-19], since dynamic floor fields, i.e. fields, which take pedestrians into account, are computationally too expensive. However using static floor fields results in artificial movement patterns. Nevertheless, some approaches use these dynamic fields

([20], [21], [22]). On the large-scale, graph-based algorithms assign edge weights without distinction between visible and invisible edges, which we believe is provides more information than actually available for human individuals and thus does not correctly reflect human perception (c.f. Fig. 1).

3 Setup of the new hybrid multi-scale model

The proposed hybrid multi-scale model consists of two layers; a schematic setup of the model is shown in Fig. 2.
The small-scale layer consists of a cellular automaton. This automaton is composed of hexagonal cells, each of them having the size of an average European male. Pedestrians move on these cells following simple rules that depend on different cell values. In the simplest case these are given as a sum of a navigation field and a repulsive pedestrian field. The navigation fields are derived from dynamic floor fields, which are calculated based on the Fast Marching Method (FMM) [23]. Summing up local repulsions of all other pedestrians, the repulsion field is obtained. The large-scale layer is formed by a navigation graph [5], which is derived automatically from the scenario's geometry. Based on this graph, different routing algorithms are implemented to reflect different navigational behavior.

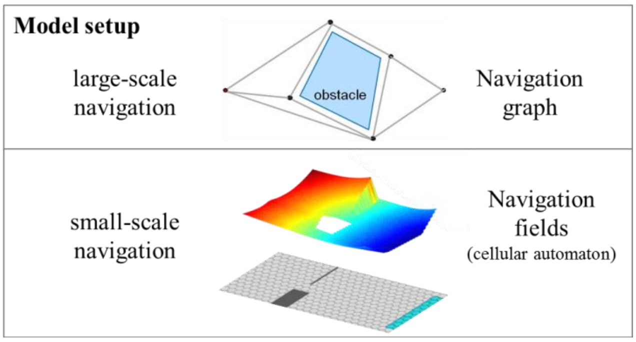

Fig. 2. Setup of the two-layered simulation model

3.1 Information exchange from navigation layer to locomotion layer

Instead of calculating one dynamic floor field for each destination, which covers the whole area of the scenario, vertices from the navigation graph serve as intermediate destinations. This enables the division of the scenario area into many small floor fields. The advantage of having many small fields is that only those fields have to be updated where pedestrians are located on. This results in lower computational time, since only small areas have to be updated. A second advantage comes into play, if the directions of the edges of the graph are considered: Since navigation graphs are directed graphs towards the destination, directed floor fields can be created by sorting the cell values x_i according to a key $\kappa(x_i)$, which combines travel times and distance to origin [24]:

$$\kappa(x_i) = \alpha T(x_i) + (1 - \alpha)\beta d(x_i, V^O), \quad (1)$$

where $\kappa(x_i)$ denotes key the values are sorted by, $T(x_i)$ is the time to reach cell x_i; V^O stands for the origin vertex and $0 \leq \alpha \leq 1$ and $\beta > 0$ are appropriate constants. The difference between an undirected and a directed floor field is depicted in Fig. 3 for different values of α and β. One can see that the choice of α has to be made carefully in order to still obtain a sufficient number of cells being covered by the field.

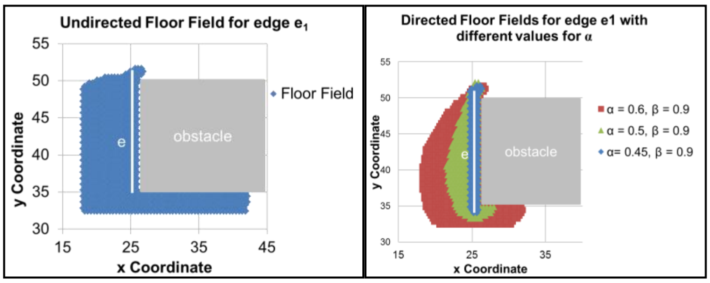

Fig. 3. Comparison between undirected floor field for edge e and directed floor fields for different values of α

3.2 Information exchange from the small-scale layer to the large-scale layer

In current multi-scale models, edge weights for the graph layer are simple distances or travel times, the latter being derived from densities on the edges. Local densities can be accessed easily in cellular automata, since the neighborhood of each pedestrian is known and the occupied cells can be counted. From the determined density, the pedestrians' velocity on the particular edge is derived by means of a fundamental diagram, and the corresponding travel time is used as edge weight. However due to the local nature of densities, resulting travel times may be in inaccurate. This becomes apparent, if only a small part of the edge is congested, i.e. due to a bottleneck. Using mean velocity values may be too optimistic, while taking the minimum velocity results in too pessimistic estimates. Additionally, pedestrians taking a detour in order to avoid congestions cannot be captured.

Taking values from the dynamic floor field improves the estimates significantly. Instead of using velocities and distances to derive travel times, the floor field values from the vertex cells reflect the travel time explicitly. An example that illustrates this improvement in realism of the simulations is given in Fig. 4.

Nevertheless, applying these floor field values as edge weights for all edges of the entire navigation graph would result in unrealistic behavior, since this implies that individuals have global knowledge of the current situation in the entire scene. However, as pedestrians are only able to take congestions into account, which are visible from their current position, a distinction has to be made between visible and invisible edges. This can be achieved easily in a pre-computational step, since a visibility graph is applied. Taking the Euclidean distance for invisible edges and the floor field values for visible edges improves the realism of the calculated routes, when implementing a fastest path strategy.

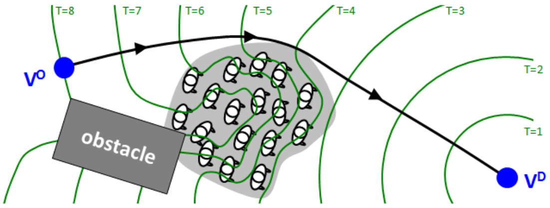

Fig. 4. Schematic sketch of a dynamic floor field estimating travelling times of pedestrians travelling form the origin V^O to the destination V^D.

An overview of the overall information exchange flow within the hybrid multi-scale model is given in Fig. 5.

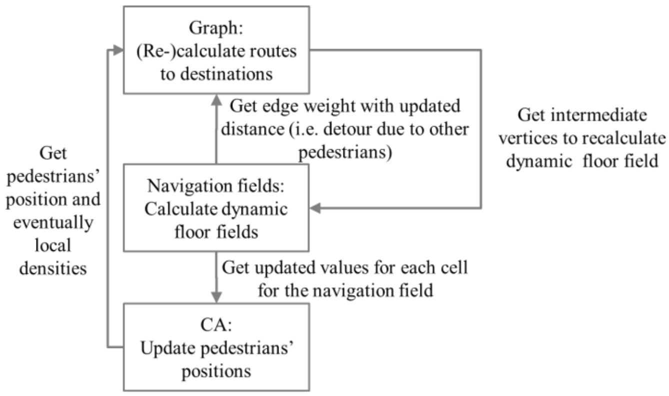

Fig. 5. Interaction between the layers of the hybrid simulation model

4 Tests

To illustrate the improvements resulting from the proposed hybrid model, two test cases are presented. All presented simulations rely on the microscopic pedestrian simulator introduced in [16]. For further references we refer also to [25–30].

The first scenario consists of a corridor around a corner; three different simulations have been considered. First, static floor fields have been used, not taking into account other moving pedestrians. The second simulation has been based on dynamic floor fields without using the vertices from the navigation graph as intermediate destinations. The third simulation has combined the graph with floor fields. Results for the different simulations are shown in Fig. 6.

One can see that using static floor fields results in unrealistic patterns. Pedestrians are jamming in front of the corner, while they could walk around the other pedestrians in order to steer around the congestion. The second and third simulation produce more realistic results: The whole width of the corridor is used and no artificial congestion occurs at the left side of the obstacle. Furthermore, one can also observe that the quality of the results is not reduced when using intermediate destinations, although significantly less computational time is required for updating the floor fields.

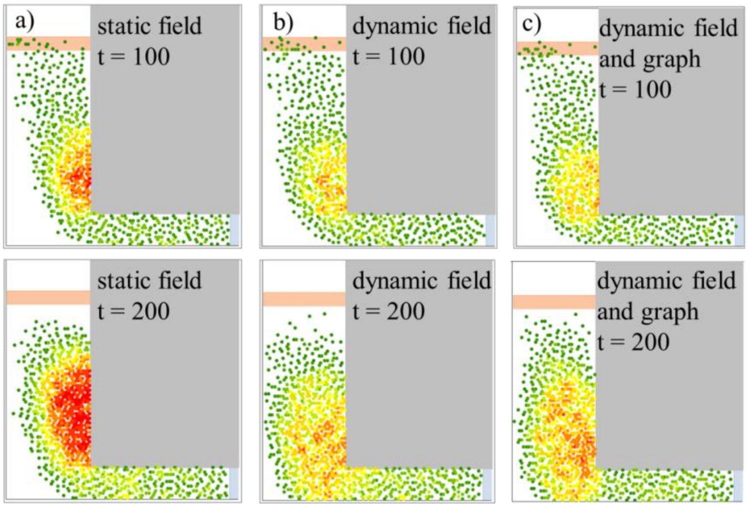

Fig. 6. Simulation screenshots after 100 and 200 seconds: (a) snapshot with static navigation field; (b) snapshot with an undirected dynamic navigation fields; (c) snapshot with directed dynamic navigation field in combination with a navigation graph

The second test case we have considered illustrates the importance of distinguishing between visible and invisible edges and thus assigning different edge weights to both sets. The scenario consists of several obstacles and a bottleneck, which is not visible from the origin (c.f. Fig. 7).

If visible and invisible edges are not distinguished, pedestrians detect a new fastest path leading around the south corner of the obstacle when the congestion in front of the bottleneck forms. This does not seem to be realistic, since pedestrians at the origin typically would not know about the congestion at the bottleneck. If the distinction between visible and invisible edges is introduced, pedestrians are walking around the north corner of the first obstacle, realizing the congestion and then decide to walk around the south corner of the second obstacle. This seems to be a more natural behavior. All simulation results are visualized in Fig. 7.

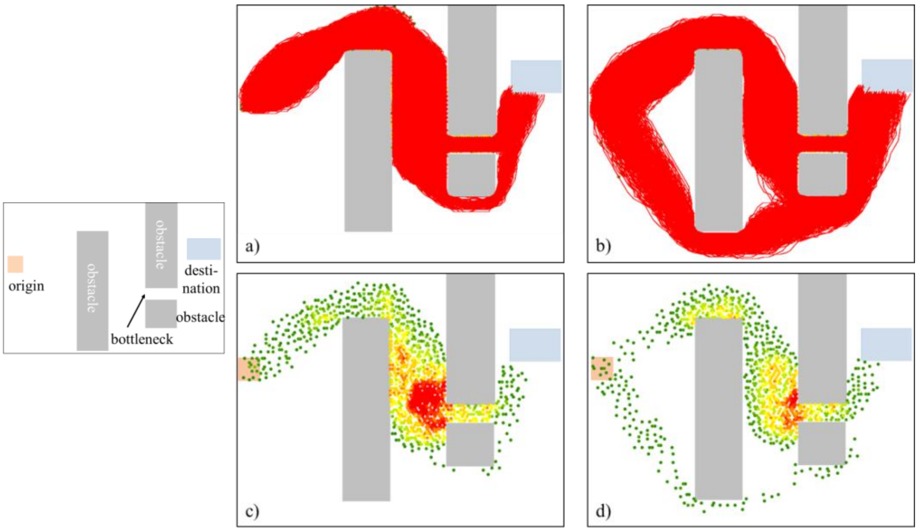

Fig. 7. Left: Scenario of the test case: There are several obstacles and a bottleneck which is not visible from the origin. Right: Simulation results: (a) traces of all pedestrians for the simulation with distinguishing between visible and invisible edges; (b) traces of all pedestrians for the simulation without distinction; (c) simulation screenshot of the simulation with distinction between visible and invisible edges; (d) simulation screenshot for the simulation without distinction

5 Conclusions

In this work a new hybrid multi-scale model has been proposed, which combines a small-scale locomotion layer with a large-scale navigation layer in order to overcome the limitations of existing multi-scale models: Using static floor fields for modeling small-scale aspects leads to artificial movement patterns. Calculating dynamic floor fields – i.e. taking into account moving pedestrians - results in a high computational time, since these fields have to be updated every time step in order to reflect the correct values. Introducing intermediate destinations from the navigation graph and dividing the scenario into many small floor fields results in significantly reduced computational effort, since only a few fields have to be updated, namely only those where (many) pedestrians are located on. At the same time, a significant improvement for estimating travel times on individual edges is achieved when compared with static floor fields or density-based approaches. On the large-scale, most simulation tools simply take the fastest path to calculate the routes for the pedestrians. Imprecise estimates lead to routes, which can be misleading. Taking values from the dynamic floor fields for visible edges instead, leads to a more precise estimate for edge weights and thus to more accurate routes.

The presented examples show that this close coupling between the small-scale and large-scale navigation decisions leads to significantly more realistic simulation results than achievable with conventional multi-scale approaches.

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