How Do Pedestrians find their Way? Results of an experimental study with students compared to simulation results

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Abstract – In our contribution we present results of an experiment about route choice and spatial orientation of pedestrians, which we compare with simulation results from a microscopic model for pedestrian simulation. To map large-scale orientation of pedestrians, we extended this model by a navigation graph. We describe the basic model as well as the graph layer extension. We use this graph as a basis for different routing algorithms, thus modeling different types of pedestrians, for example ones being familiar and ones being not familiar with the location. We discuss the results of the experiment and simulation and give an outlook for further improvement of our algorithms for a better simulation of the empirical data.

Introduction and Related Work

Simulation of pedestrian crowds for both normal and evacuation situations has been widely examined. There exists a variety of different approaches - each focusing on a different objective. One possible categorization is to distinguish between macroscopic and microscopic models as proposed in (Schadschneider et al. 2009).
Macroscopic models focus on overall situations of simulated scenarios, working with mean values for velocities, densities etc. Examples for such models are network-based models to derive minimal evacuation times (Hamacher & Tjandra 2002) or fluid-dynamics models to simulate pedestrian flows (Henderson 1974).
Microscopic models consider each individual and model interaction between the individuals. Their objective is to examine local phenomena like lane formations or bottlenecks and their influence on evacuations. One representative for microscopic models is the Social Force Model (Helbing & Molnár 1995). Microscopic models can be further distinguished into continuous models and space-discretized models (e.g. cellular automata).
All these different approaches make assumptions about human behaviour and put these assumptions into models and algorithms. But the validation of these models is difficult, as very few empirical results exits for comparison. We carried out an experiment with students focusing on way finding behaviour and spatial orientation to retrieve empirical data for comparison with our simulation.

Model description

In our project we focus on regional evacuation. We employ a microscopic model that uses potential fields to describe the influencing forces of each pedestrian (attracting force of the destination, repellent forces of obstacles as well as repellent forces of other pedestrians) as described in (Klein, Köster & Meister 2010). The space is discretized using a cellular

automaton with hexagonal cells. A detailed description of pedestrian navigation on this automaton can be found in (Hartmann 2010).
This combination forms the microscopic navigation layer for the pedestrians and is focused on interaction between pedestrians to model local phenomena such as lane formation and bottlenecks. Using a cellular automaton, the simulation can be speeded-up such that the simulation can be run in real-time.
Since the objective of our simulator is simulating large-scale areas, we introduce a high-level navigation layer, describing the large-scale orientation of pedestrians. To realize this, a navigation graph is used which consists of intermediate destinations as vertices, which are connected by edges, if two vertices are in line of sight to each vertex. The automatic derivation of this graph from a given scenario is described in (Kneidl, Borrmann & Hartmann 2010). This graph is used as the basis for implementing different routing algorithms, which map different pedestrian types (e.g. pedestrian who are / who are not familiar with a location).

Experimental Setup

We carried out an experiment with students at our university. The task for the students was to walk in small groups (2-4 students) from the campus to a well-known destination in the Munich city centre without carrying any map for orientation. To prevent the students to walk in one big group, we let them start from different corners around the campus with a certain delay. The starting points and the destination are illustrated in Fig. 1.

The following instructions were given:

- Gather in groups of 2 to 4 people
- At the starting point, you have the possibility to have a look on a map
- Go without a map for orientation
- Document each street crossing you pass

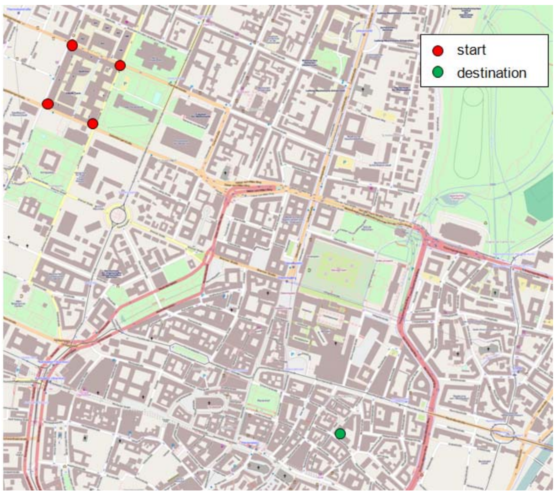

Fig. 1 Munich city centre map (available from www.openstreetmap.org) with start and destination

After their return to the campus each student had to fill out a questionnaire about way finding and orientation. They all drew their chosen route into a map for documentation.
In total, 92 students joined the experiment, divided into 31 groups. The distribution of the group size is given in Table 1.

Group Size	Number of Groups
1	2
2	9
3	9
4	10
5	1

Table 1 Distribution of the group size

Simulation setup

Scenario derivation

To simulate the experiment, it took several steps to derive a scenario from a street map: starting from an open street map of the interested area (available from www.openstreetmap.org) the map was converted into a black and white image. From the black and white pixeled map the scenario for the simulation was derived, such that each cell of the cellular automaton is accessible if the centre pixel of a cell is not black. This was done to be able to run the simulation on this large area (size: 1.7 x 1.8 km^2) efficiently. Once having the scenario created the navigation graph was derived by placing vertices at each street crossing and connecting each two adjacent vertices with an edge. The three steps of scenario derivation are summarized in Fig. 2.

Fig. 2 Derivation of scenario from an open street map

Routing algorithms

In our simulation we distinguish between three types of pedestrian with different orientation capabilities:

- Pedestrian who are familiar with the location and know the best way to their destination
- Pedestrians who are not familiar with the location, but try to keep as close as possible to the airline to their destination
- Pedestrians who are not familiar with the location and make their decisions based on local criteria

We implemented these different types using three different algorithms, namely the *Fastest Path Algorithm*, the *A*-Algorithm* and *Probabilistic Choice Algorithm*. These three algorithms are described briefly in the next three subsections.

Fastest Path Algorithm

The Fastest Path Algorithm is based on the Dijkstra (Dijkstra 1959) shortest path algorithm. It assigns travel times as edge weights. These travel times are derived from the length of an edge and the mean velocity of all pedestrians walking on it. Since the mean velocity depends on the density on an edge, the fundamental diagram of Weidmann (Weidmann 1993) - which maps mean densities to mean velocities – is used to derive the corresponding velocity. As densities can change over time, edge weights will change as well and resulting from that, the fastest path changes dynamically.

A* Algorithm

To model pedestrians with no detailed local knowledge, but a good sense of orientation, a heuristic algorithm is applied for estimation of the missing details. Weights consist of two parts: one part which is known and a second part where estimated values are applied. The formula for the weight looks as follows:

$$\boldsymbol{weight_{vertex}} = \sum_{\substack{\boldsymbol{all\,edges} \\ \boldsymbol{of\ current\ path} \\ \boldsymbol{from\ start\ vertex\ to\ this\ vertex}}} \boldsymbol{weight_{edge}} + \boldsymbol{\alpha} * \boldsymbol{estimated\ weight\ to\ destination}$$

Each edge weight refers to the Euclidean Distance between the two vertices of an edge. The estimated weight refers in our case to the airline distance between the vertex and the destination vertex. In other words, at each vertex v the remaining route length to the desired destination is estimated using the airline distance, whereas the already covered distance from the start to v is known exactly. These weights are used to find the shortest path. For a detailed description of the algorithm, please refer to (Höcker et al.; Li & Höcker 2009). With the parameter α the impact of the heuristic part can be adjusted. In our case we chose α = 2.

Probabilistic Choice

The third pedestrian type refers to pedestrians that do not have a good sense of orientation. The algorithm we chose to map these pedestrians is a dialect of Ant Colony Optimisation (ACO) (Dorigo 1992). We transfer the principle of ACO algorithms to pedestrians with respect to the following points:

- Pedestrians generate trails as ants do with pheromones
- Pedestrians have no global knowledge about the topography of the surroundings – decision are made considering local conditions
- Pedestrians decide non-deterministically – probabilistic choices are able to map this non-determinism

We took these assumptions to design the probabilistic choice algorithm. Edge weights consist of two components: A non-varying part, which can be pre-computed and a varying part, which changes over time. The non-varying part consists of:

- angle derivation between the edge and the airline to the destination (see Fig. 3a)
- relative enhancement of the airline distance to the destination (see Fig. 3b)

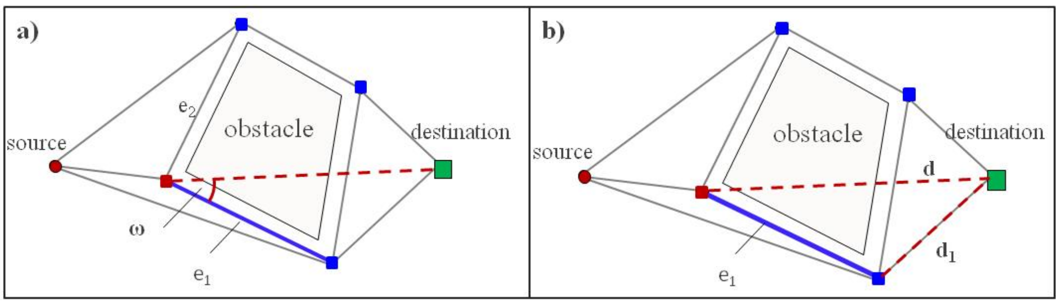

Fig. 3 a) angle derivation ω of edge e_1 b) relative distance enhancement of edge e_1: d_1/d

The varying part forms the pheromone, which is placed on each traversed edge that leads to a destination, whereby the following equation has to be satisfied at any point at any time:

$$\Sigma\ \text{Pheromone}_{\text{Graph}} = \text{number of graph edges}$$

Each edge is initialized with a pheromone unit of 1. Two parameters are used to reallocate the pheromone after each iteration (one iteration refers to one complete route from the source to a destination): *pheromone_update*, which describes the amount of pheromone that will be placed on each edge and *pheromone_decay*, a constant amount of pheromone, which decays after each iteration. For more details on the algorithm, please refer to (Angus 2005).
The assembled weight looks as follows:

$$\boldsymbol{weight_{edge} = \omega^{\alpha} * relativeEnhancement^{\beta} * pheromone^{\gamma}}$$

α, β and γ are weighting factors to influence the impact of each of the three components. In our simulation we chose $\alpha = 3$, $\beta = 3$ and $\gamma = 4$.
The edge choice is probabilistic, using the roulette wheel selection (Bäck 1996): the sum of all weights of all outgoing edges is scaled to a value between 0 and 1 – the bigger the weight, the higher the value. This means – mapped on a roulette wheel where each section of the wheel refers to an edge value – the higher the value, the bigger the sections. Then the roulette wheel is turned and the edge, at which section the wheel stops turning, will be selected.

Comparison of result and experiment

In Fig. 4 all routes of the student groups for each starting point are plotted. Each route is displayed in a different colour.
We can observe the spread of the chosen routes from this representation very well. There is no clearly preferred route visible. In the survey we asked the students: "How familiar are you with the Munich city centre?" 51.44 percent answered that they are very familiar, quite familiar or familiar with the Munich city centre. This explains the spread of the routes to some extent. Another conclusion from the results is, that pedestrians do not decide deterministic and have different spatial perception. Although they all had the same destination, different routes were thought to be the shortest route. 89.54 percent believe that they have chosen the shortest way.
Fig. 5 shows the results of the simulation. The white lines represent the traces of the simulation results for the pedestrians. The wider the white line, the more pedestrians traversed this edge. We observe that the simulation does not completely reflect the reality.
The *Fastest Path Algorithm* and the *A* Algorithm* are deterministic algorithms - which means that each produces only one optimal path according to a given criteria - from each starting point to the destination. But we can conclude from the experimental results that pedestrians do not walk in a deterministic way. This non-deterministic behaviour is not reflected by the algorithms.
The *Probabilistic Choice* algorithm on the other hand produces too many routes. This is due to the probabilistic choice of the routes and the few iterations (=routes) the algorithm has calculated. There have not been created enough routes such that the placed pheromone has a sufficient impact of the quality of an edge.
Although we do not see a perfect match between the simulation and the reality, we still can state that the basic idea of the algorithms is correct. All three algorithms find routes which were followed by the students. The weakness of the deterministic algorithms is, that they can only find one solution for each source-destination pair. On the other hand, the spread produced by the probabilistic algorithm is too large.
We can conclude from the experiment that we have to consider more parameters than just distance to destination and angle derivation. In the survey the students stated that their route mainly consisted of main roads (77.12 percent) and that they prefer less turns on their route

(73.20 percent), which can be observed from the plot as well. So far, this preference is covered only indirectly from the algorithms.

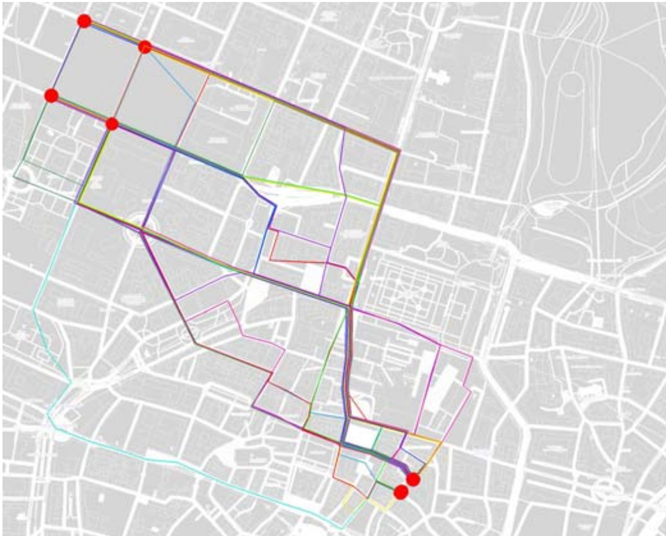

Fig. 4 Resulting routes from the experiment

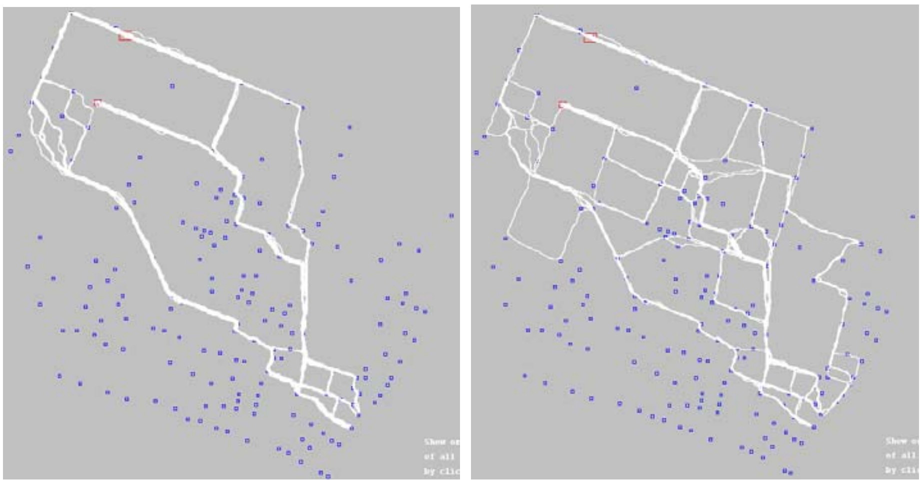

Fig. 5 a) Simulation results of Fastest Path algorithm and A* Algorithm: The white lines refer to the traces of the simulated pedestrians b) Simulation results of the Probabilistic Choice Algorithm

Summary and Outlook

In our contribution we presented results of an experiment, which we carried out with students at our university. The objective of this experiment was to get empirical data for comparison with our routing algorithms. These algorithms were implemented on top of a microscopic model for pedestrian simulation, which we extended by a navigation graph to map large-scale orientation of pedestrians.
The results of the experiment show a wide variety in the route choice of the pedestrians. Two of our implemented algorithms are deterministic and therefore always find one optimal path according to given criteria. The third algorithm finds a very large variety of routes, taking into account the non-deterministic choice behaviour of humans. We can conclude that our algorithms do not perfectly model the reality. There are more features which have to be taken into account and can be derived from the answers the students gave at our survey. These answers have to be analyzed further. The results from the analysis will then be used to adapt our algorithms.

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