A Unified Pedestrian Routing Model for
Graph-Based Wayfinding
Built on Cognitive Principles

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The wayfinding behavior of pedestrians in street and building networks can be predicted by computer simulations based on routing models. To model realistic routing behavior, it is necessary to integrate spatial- and social-cognitive aspects into the wayfinding models. However, a model that incorporates diverse influencing factors on pedestrian route planning has yet not been developed for microscopic simulations. We present a unified routing model that describes pedestrian route choices in street and building environments by integrating spatial- and social-cognitive aspects. We achieve an integration of both domains by combining different graph-based routing methods, each formalizing a cognitive theory. In addition, we present a calibration method for the spatial-cognitive aspects. For validation purposes, we use the model to simulate how the visitors of a music festival navigate to the event and how people navigate in a city district. Our methodology is highly flexible and can be extended to include other aspects of wayfinding behavior.

Keywords: pedestrian behavior modeling; pedestrian behavior simulation; cognitive-modeling; model integration; graph-based wayfinding

1. Introduction

Research on pedestrian dynamics and microscopic behavior simulations is a field in which models can typically be viewed from three different but interconnected perspectives (Hoogendoorn, Bovy, and Daamen 2002; Bierlaire and Robin 2009). Operational models describe how pedestrians walk and move as individuals and in groups (Peters and Ennis 2009; Moussaïd, Helbing, and Theraulaz 2011). Tactical models focus on the wayfinding and route planning behavior of pedestrians in network environments, e.g. buildings or cities (Höcker et al. 2010; Kneidl 2013). Strategic models describe how destinations are selected and activity schedules are found (Dijkstra and Jessurun 2014; Danalet and Bierlaire 2015). Furthermore, from the point of view of spatial-cognitive science, tactical and operational behavior is defined as ‘navigation’ and tactical behavior is in general described as ‘wayfinding’ (Wiener, Büchner, and Hölscher 2009).

Computer simulations are being developed in order to predict wayfinding behavior of pedestrians (Kemloh et al. 2012; Kneidl and Borrmann 2011; Hartmann 2010). However, individual route planning is influenced by spatial-cognitive (Wolbers and Hegarty 2010) and social-cognitive (Raafat, Chater, and Frith 2009) aspects, which are not included...
jointly in pedestrian routing models. Thus, at present and to the best knowledge of the authors, no pedestrian wayfinding behavior model includes all aspects of pedestrian route choice in a single model.

In a previous research by Kneidl (2013), different aspects of spatial-cognitive-based wayfinding behavior were successfully modeled, and four different graph-based pedestrian route planning algorithms, each of which depicts a specific type of wayfinding aspect, were presented. However, as shown by research into spatial cognition, human wayfinding abilities are more fine-grained (Golledge 1999; Wolbers and Hegarty 2010; Hölscher, Tenbrink, and Wiener 2011). Apart from the aforementioned wayfinding patterns, two herding algorithms were described by Kneidl (2013). These herding concepts were also independently modeled using graph-based methods. However, to date, there is no comprehensive approach to combine the previous six algorithms. To overcome this deficiency, we present the Unified Pedestrian Routing Model (UPRM), which merges the six routing methods into a single model and extends the previous version of the UPRM (Kielar et al. 2015). Hence, the model describes how spatial-cognitive mechanisms influence wayfinding behavior and how social phenomena such as herding intertwine with individual routing. We also implemented the UPRM in the pedestrian simulation framework ‘MomenTUMV2’. Thus, all presented simulations were conducted with the ‘MomenTUMv2’ simulator. For details on the framework, we refer to Kielar, Biedermann, and André (2016).

The developed UPRM approach for pedestrians integrates cognitive wayfinding strategies and can be applied in network-based environments. In the addressed wayfinding scenarios, pedestrians find a route from a starting location to a destination to navigate through the network of a city or a building. Typically, the actual destination cannot be seen from the starting point, but pedestrians will have a rough idea of the goal’s location. Furthermore, the routes for the pedestrians are determined in a microscopic (agent-based) manner (Helbing et al. 2005; Raubal 2001; Wooldridge 2009).

By applying the presented approach to pedestrian simulations, a more diverse range of pedestrian wayfinding behavior can be correctly simulated. Furthermore, our integrative approach serves as a framework that can include further aspects of pedestrian routing behavior by extending the mathematical formulation of the UPRM.

The remainder of this paper is organized as follows. In Sec. 2, we discuss previous work related to pedestrian routing models and describe the importance of the spatial- and social-cognitive mechanisms we address. The six graph-based algorithms integrated into the proposed model are discussed in Sec. 3. The proposed UPRM is presented in Sec. 4. We present validation and simulation studies in Sec. 5, and conclude this paper with a discussion and closing remarks.

2. Related work

Here, we provide a brief overview of pedestrian wayfinding behavior models and describe the mandatory spatial- and social-cognitive foundations that influenced our work. We address the graph-based search methods in Sec. 3 and refer to additional literature on graph algorithms (Gross and Yellen 2005). For an introduction to cognitive psychology, we refer to Anderson (2010).

2.1. Pedestrian routing models

In contemporary research of pedestrian dynamics and geographical information science, there are several different approaches to model pedestrian wayfinding behavior. Graph-
based models are well-known approaches that are used in combination with routing algorithms to determine an ordered set of street or building network links that describe a pedestrian routing path (Raubal 2001; Gaisbauer and Frank 2008; Höcker et al. 2010; Thill, Dao, and Zhou 2011; Kemloh et al. 2012; Kneidl 2013). Graph-generation algorithms serve to define the underlying routing network for routing algorithms based on the simulation scenario geometry (Geraerts and Overmars 2006; Kneidl, Borrmann, and Hartmann 2012) or geographical data (Kasemsuppakorn and Karimi 2013; Neis and Zielstra 2014). An alternative approach to route planning is to be seen in the ‘floor field method’ and its derivations (Burstedde et al. 2001; Hartmann 2010; Guo, Huang, and Wong 2013). These methods compute distances on a grid that covers the simulation scenario as an underlying data structure. Each grid cell can hold values – dynamic or static ones - that are subject to gradual changes, e.g. in terms of destination proximity or ground floor accessibility. Thus, floor field methods provide a routing path from an origin to a destination, based on the computed potential. In addition to routing approaches from pedestrian-related research, other fields approach wayfinding behavior from different perspectives. For example, Sud et al. (2008), as well as Geraerts and Overmars (2007) focus on route planning methods from a computer graphics perspective. Geraerts and Overmars (2007) describe the ‘corridor map method’, which uses a route map graph and clearance information to construct a corridor covering the traversable scenario layout from an origin to a destination. When the corridor is complete, the steering behavior, a combination of wayfinding and walking, is performed inside the corridor boundaries towards a given destination. The robotics community has performed research that is heavily focused on routing (Tani 1996). While the resulting optimal routes are highly desirable for navigating robots and non-human virtual characters, these approaches are mostly not suitable to simulate human behavior, as human wayfinding is suboptimal in all non-trivial wayfinding cases – due to peoples’ cognitive capabilities.

Herding behavior, a common phenomenon in pedestrian dynamics, has been discussed in a number of research publications. Some models include social group behavior, queuing, or group cohesiveness, which can be understood as herding behavior (Pan et al. 2007; Seitz, Köster, and Pfaffinger 2014; von Sivers et al. 2014; Kneidl 2015). However, the herding behavior we address in this paper focuses on herding emerging during wayfinding. A number of methods to describe herding during wayfinding have been proposed already. For example, Schadschneider, Kirchner, and Nishinari (2003) as well as Kneidl and Borrmann (2011) describe methods that are based on the concept of the ‘Ant Colony Optimization’ algorithms. Another approach is the concept of fastest paths, where pedestrians attempt to find promising paths by following other pedestrians who walk fast (Kneidl and Borrmann 2011). Generally, herding in wayfinding has been modeled before. Nonetheless, an integrative framework including the herding aspects with spatial-cognitive theories has yet not been proposed.

Other researchers also propose concepts for routing based on spatial-cognitive factors. However, they did not model intermediate routing variants (Kneidl 2013; Tan, Wu, and Lin 2015) or do not include social factors (Andresen et al. 2016).

2.2. Spatial-cognitive concepts

Extensive research into spatial cognition helps to develop an understanding of people’s route planning limitations (Wolbers and Hegarty 2010; Hölscher, Tenbrink, and Wiener 2011). Human wayfinding abilities depend on an accurate perception of spatial information, the competence to generate a spatial representation of the environment, and an efficient utilization of the spatial representations (Wolbers and Hegarty 2010). Generally, spatial representations of environments are denoted as cognitive maps. Thus, wayfinding
abilities are directly related to the construction and processing of such maps (Golledge 1999).

Research into spatial-cognitive abilities has proven that people use route-based, survey-based, or fuzzy intermediate strategies for route planning (Golledge 1999; Wolbers and Hegarty 2010; Wen, Ishikawa, and Sato 2013). In route-based wayfinding, a sequence of egocentric actions must be performed to recreate a route. Thus, little overall knowledge about the environment and the relation between locations is required. In contrast, survey-based wayfinding is an allocentric strategy. People who use this strategy have a general understanding of relations and distances within a certain area. Thus, they can find new paths with ease.

However, humans do not simply choose one of these two strategies. Instead, they generate intermediate and mixed routing solutions based on the integrity of their cognitive map, the reliability of their memory retrieval processes, their ability to apply information to actions, and the route planning task at hand (Wolbers and Hegarty 2010; Hölscher, Tenbrink, and Wiener 2011; Golledge 1999). This indicates that intermediate variants of wayfinding methods must exist. The proposed UPRM captures these intermediates variants of route- and survey-based wayfinding behavior in a single model.

2.3. Social-cognitive concepts

In order to describe herding behavior during wayfinding, we rely on findings of social cognition research. Herding in humans can be found in multiple domains, e.g. economics, crowd behavior, or social networks. Herding appears without a central control system (Raafat, Chater, and Frith 2009); thus, patterns emerge based on a system of individuals. Raafat, Chater, and Frith (2009) provided a theoretical framework comprising pattern- and transmission-based approaches as modeling concepts for herding. Whereas transmission-based models focus on the propagation of the emerging phenomena in a group, pattern-based models focus on generating the emerging phenomena by a set of rules that every individual follows. Our approach is pattern-based, as we provide two heuristic rules that influence herding in route choice.

Frith and Frith (2012) claim that social cognition is fundamentally connected to learning from others and that implicit and explicit learning behavior processes are among the primary mechanisms of social cognition. Explicit processes comprise communication with others, whereas implicit processes are mainly built upon observing other people. By observing, an individual can learn from others without engaging in trial and error procedures. We assume that pedestrian will copy the routing behavior of others, e.g. to avoid walking into dead-ends or to find a destination for which the exact route is not known. We apply this theory in our approach for herding in routing and build upon the assumption that implicit processes of observing and copying other peoples routing behavior will foster herding behavior. A set of experiments performed by Dyer et al. (2009) served to evaluate the knowledge gap leading to herding phenomena in human crowds. They showed that only a few leading peers in a group provide efficient herding crowd motion. To summarize, our proposed social-cognitive herding approach is based on the fundamentals of observing others and copying their behavior.

3. Underlying routing methods

As described in Sec. 1, we present a new and cognition-based approach to model human wayfinding. We use a graph presentation of the space for the algorithmic implementation of the model. To create graphs, we apply graph generation algorithms that use
the environment, e.g. buildings and walls, in a polygon representation to derive routing graphs that comprise edges and vertices (Kneidl, Borrmann, and Hartmann 2012). These graphs are therefore an approach to define a cognitive map of the environment. Based on graphs, wayfinding models predict the walking paths from an origin to a destination either iteratively or directly in an algorithmic manner. The distinction is based on the egocentric routing strategy (iteratively) and the allocentric routing strategy (directly) outlined in Sec. 2.2. Here, we explain the underlying graph-based routing methods that are combined in the proposed UPRM.

Direct routing solves the routing problem by finding an optimal path to the destination, based on shortest path solutions (Dijkstra 1959; Hart, Nilsson, and Raphael 1968). In contrast, iterative routing algorithms determine the next vertex to visit in a stepwise manner, based on local optima. We adjusted the direct and iterative routing methods described by Kneidl (2013). She modeled three direct routing methods, i.e Shortest Path (SP), Fastest Path (FP), and Beeline Heuristics (BH), as well as three iterative routing methods, i.e. Straight and Long Legs (SALL), Greedy Beeline Heuristics (GBH), and Ant Colony Optimization (ACO). The FP and ACO methods refer to herding during wayfinding approaches and may only be effectively applied in pedestrian behavior simulations that include many individual pedestrians.

In all routing cases, the pedestrian is informed about the location of his/her goal; thus, no search task is performed (Wiener, Büchner, and Hölscher 2009).

Figs. 1 (a - d) present example routes generated by a microscopic pedestrian simulation that applies the SP, BH, SALL, and GBH methods to an artificial scenario. Furthermore, Figs. 1(e, f) show screenshots of a pedestrian routing simulation and the underlying routing graph.
3.1. Direct routing methods

In order to integrate direct routing models, we build upon two direct routing methods, the SP and BH algorithms (Kneidl 2013). Both methods model the routing behavior of pedestrians with profound knowledge of the street network and therefore allocentric routing strategies.

The SP method is based on Dijkstra’s algorithm (Dijkstra 1959) and describes the tendency of finding the shortest route to a destination (Kneidl and Bormann 2011; Hölscher, Tenbrink, and Wiener 2011; Kneidl 2013). The weight calculation method of the SP combines the distance \( d_{ij} \) between current vertex \( i \) and successor vertex \( j \) along a directed edge \( e_{ij} \).

\[
w_j = w_i + d_{ij}
\]

The weight update mechanism of the BH method follows the typical update procedure in Dijkstra’s algorithm; however, we exclude the beeline distance during the update to preserve the total order in the weights. Similar to the SP method, the BH algorithm is applied each time a pedestrian visits a vertex. Fig. 2 shows an example graph that results in a vertex visiting order of 1, 4, 5, and 6 with the BH method. Furthermore, the worst-case algorithmic complexity of the BH method for a single decision is defined by the complexity of Dijkstra’s algorithm – using a list – is \( O(V^2) \), in which \( V \) is the number of vertices of the graph (Turau and Weyer 2015).

The BH algorithm is based on the A* algorithm (Hart, Nilsson, and Raphael 1968) and describes the tendency to follow a beeline toward a destination. Dalton (2003); Conroy (2001); Hölscher, Tenbrink, and Wiener (2011) showed that people apply this kind of wayfinding strategy. The algorithm to calculate the weight of the BH routing method integrates the beeline distance \( d_{jg} \) from the next vertex \( j \) to destination vertex \( g \), the distance \( d_{ij} \) between current vertex \( i \) and a successor vertex \( j \), and a constant \( \beta \). Here, \( \beta \) models the influence of the beeline distance to the goal location regarding the distance to the next vertex. Based on test simulation, we use the constant factor \( \beta = 1.5 \), which describes that the beeline influence is \( 1/2 \) times stronger than the distance influence. Note that we omit the random distance estimation error\(^1\) presented by (Kneidl 2013).

\[
w_j = w_i + d_{ij} + d_{jg} \cdot \beta
\]

\(^1\)We removed the error term because it creates non-deterministic noise to the model and tends to obstruct proper validation. We are investigating this error term and our current hypothesis is that this is strongly related to the angular and distance error in human perception.
3.2. Iterative routing methods

In order to integrate iterative routing models, we build upon the iterative routing concepts of the GBH and SALL methods (Kneidl 2013), which model the routing behavior of pedestrians who are unfamiliar with the street or building network and therefore egocentric routing strategies.

The SALL method models the tendency to walk along straight and long streets; thus, reduce the number of turns Golledge (1995); Dalton (2003); Hölscher, Tenbrink, and Wiener (2011). The route choice of the SALL method is based on the angle $\gamma_{a_{ij}} \in [0, \pi]$ between the last vertex $a$ and the next vertex $j$, as well as the relative distance reduction $d_{jhg}/d_{jg}$ to the destination vertex $g$. The value $d_{jhg}$ is calculated based on the vertex $h$, which is the farthest vertex within the projection of an arc of the angle of $\pm \mu$. The arc is centered along $e_{ij}$ and its successor edges and their successor edges in succession. We set $\mu$ to $\pi/9$. The angle $\gamma_{a_{ij}}$ improves the weight in the case of straight roads. The successor vertex with the smallest result is selected as the next vertex to visit.

$$w_j = (1 - \alpha) \cdot (d_{jhg}/d_{jg}) + \alpha \cdot (1 - \gamma_{a_{ij}}/\pi)$$ (3)

The parameter $\alpha$ can take a value between zero and one. We set $\alpha = 0.75$ to increase the influence of the angle term of Eq. 3. If the value of $\alpha$ approaches one, the pedestrian will strictly follow straight routes. In test simulations, we found that $\alpha = 0.75$ provides the most stable straight and long route following behavior, including natural direction changes if the route deviates strongly from the goal direction. Fig. 3 shows an example graph that results in a vertex visiting order of 1, 3, 5, and 6 with the SALL method, with $d_{jhg}/d_{jg} = 1.44/4.01$ for $j = 3$, $h = 5$, and $g = 6$. Furthermore, the worst-case algorithmic complexity of the SALL method for a single decision is $O(V^2)$, in which $V$ is the number of vertices of the graph. The complexity is based on the maximal number of follower vertices $V - 1$ of the current node $v_i$ and the maximal number of successor vertices of each follower vertices that connect $v_i$ to the farthest vertex.

The GBH describes a BH approach for pedestrians who are unfamiliar with the street network. The theoretical groundings of this wayfinding strategy are based on the same research as the BH concept (Dalton 2003; Conroy 2001; Hölscher, Tenbrink, and Wiener 2011). In the route choice of the GBH method, the vertex with the smallest weight $w_j$ is selected as the next vertex to visit. The weight is only influenced by the beeline distance $d_{jg}$ from a successor vertex $j$ to the destination $g$.

$$w_j = d_{jg}$$ (4)

Fig. 3 shows an example graph that results in a vertex visiting order of 1, 4, 5, and 6 with the GBH method because the beeline distance between 4 and 6 is the shortest. Furthermore, the worst-case algorithmic complexity of the GBH method for a single
decision is $O(V)$, in which $V$ is the number of vertices of the graph. The complexity is based on the maximal number of follower vertices $V - 1$ of the current node $v_i$.

### 3.3. Herding routing methods

We apply the approaches of the FP and the ACO methods to describe herding behavior (Kneidl 2013). Each method provides a heuristic rule according to which a pedestrian will select the next vertex to walk to. Regarding the aspect of herd-like routing behavior, both methods include information about other pedestrians in sight. Thus, approaches like this can only be applied effectively in a system with multiple pedestrians. We condensed both models to an iterative routing method. However, applying these models as single routing methods will yield unacceptable routing results.

The FP method applies a velocity $v_{ij}$ to each adjacent edge as a weight. The velocity is based on the number of pedestrians $p_{ij}$ walking along a directed edge $e_{ij}$. In this routing model, the successor vertex with the smallest result $w_j$ is selected as the next vertex to visit.

$$w_j = 1/v_{ij} \quad (5)$$

The edge weights $v_{ij}$ are updated according to the velocities $v_{xij}$ of the pedestrians walking alongside an edge $e_{ij}$. The number $p_{ij}$ can be computed because each pedestrian holds references to the current and last edge the pedestrian walked along; thus, an update procedure can change the weight $p_{ij}$ of each edge the pedestrians are associated with. If the number of pedestrians $p_{ij}$ alongside an edge is zero, a standardized mean velocity $v_m$ is used for $v_{ij}$.

$$v_{ij} = \left(\frac{\sum_{x=1}^{p_{ij}} v_{xij}}{p_{ij}}\right)$$

The ACO method builds on the idea that herding can be modeled by pheromone-based ant colony behavior (Angus, Hendtlass, and Ali 2002; Schadschneider, Kirchner, and Nishinari 2003). Here, we model the fundamental parts, i.e., pheromone placement, pheromone following, and pheromone decay. The placement of pheromone is based on the number of pedestrians $p_{ij}$ on an edge $e_{ij}$. For this approach, we apply an upper pedestrian

![Figure 3. Example graph with distances between vertex 3 and 6 as well as the deviation angles of the follow-up edges from the direct walking direction.](image)
limit $m$ that models the maximal amount of pheromone on an edge. Thus, the method updates the pheromone level $a_{ij}$ on an edge equal to the number of pedestrians if their number is below the upper limit $m$. If the current number $p_{ij,t}$ of pedestrians on an edge drops below the upper limit, the pheromones decay over time.

$$a_{ij,t} = \begin{cases} a_{ij,t-1} - \Delta t \cdot \varsigma, & p_{ij,t} < m \\ m, & p_{ij,t} \geq m \end{cases} \quad (7)$$

The parameter $\varsigma > 0$ models the linear decay rate of the pheromone over time, which is discretized into steps of $\Delta t$. If the parameters $\varsigma$ and $m$ are not properly balanced, the herding behavior is over- or underrepresented. Thus, both parameters must be calibrated by field data.

Pedestrians will walk along an edge $e_{ij}$ to a successor vertex $j$ starting from vertex $i$ if the edge exhibits the highest amount of pheromone $w_j$ compared to the neighboring edges:

$$w_j = a_{ij} \quad (8)$$

4. Routing behavior modeling

The UPRM integrates the routing methods described in Sec. 3. As a result, the integration is not a mutually exclusive application of the routing algorithms but a mathematical-based integrative concept. This is achieved in two steps. First, we model the integration of the direct and iterative methods without herding behavior and present a calibration approach. Then, we extend the model using the herding concepts.

4.1. Spatial-cognitive modeling

The spatial-cognitive UPRM is an iterative routing method that models the route-choice decision behavior of selecting the next vertex $j$ to visit at a network junction. The method integrates the four basic algorithms, i.e. SP, BH, GBH, and SALL. The weight calculation for the UPRM is expressed as follows:

$$w_j = \zeta \cdot w_j^{SP} + \eta \cdot w_j^{BH} + \kappa \cdot w_j^{GBH} / \max (w_j^{GBH}) + \psi \cdot w_j^{SALL} / \max (w_j^{SALL}) \quad (9)$$

The method selects the successor vertex $j$ of the current vertex $i$ with the smallest weight $w_j$ as the next vertex to visit. This approach is similar to the previous iterative methods.

The UPRM integrates the GBH and SALL methods by assessing the weights of all adjacent vertices $j$ of vertex $i$. These weights are normalized by the maximal weight of all successor vertices of vertex $i$. Note that this is performed separately for the GBP and SALL methods. The SP and the BH methods contribute temporary calculations of optimal paths, starting from vertex $i$. The first vertex of each optimal path is compared to the adjacent vertices $j$ of the current vertex $i$. If a successor vertex $j$ is part of the optimal path, the weight $w_j^{SP}$ (or respectively $w_j^{BH}$) is zero; otherwise, it is one.

The resulting weights for each original method are combined additively based on influencing factors. These factors describe how strongly a pedestrian is associated with a routing strategy. The factors $\zeta$ and $\eta$ model high familiarity with the route network (allocentric strategies), whereas factors $\kappa$ and $\psi$ model a lesser knowledge of the network (egocentric strategies). The values are in the range $[0,1]$; however, a single factor
with a value greater than zero is mandatory. Thus, the factor concept also models interfering knowledge and uncertainty due to overlapped or underrepresented combinations of factors. Sec. 4.2 will address the question of how to find useful factor combinations. However, it is of utmost importance to apply multiple factor combinations for wayfinding simulations. Each factor combination can determine a specific route found by a pedestrian based on the simulation scenario complexity. Thus, in wayfinding simulations, each pedestrian will be provided with a factor combination drawn from a factor combination distribution. This approach will introduce complex wayfinding behavior in a single simulation because the simulated pedestrians will behave differently.

The different wayfinding strategies are combined in Eq. 9 by a linear relationship. This approach is our initial idea of how to combine the algorithms. We choose a linear relationship because it is not clear how people integrate the different routing strategies cognitively and we do not believe that more complex relationships provide benefits. We will show in Sec. 5 that our linear approach provides promising wayfinding prediction results.

The worst-case algorithmic complexity of the simulation method is an important aspect in identifying the practical usability of the concept. Based on the worst-case algorithmic complexities of the individual methods (see Sec. 3.1 and 3.2), we can derive the overall worst-case complexity of the algorithm for a single pedestrian. In the worst case, $V$ vertices have to be visited by a pedestrian to navigate from origin to the destination. At each visited vertex $v_i$, all of the individual methods are computed. Thus, the worst-case complexity is $O(V \cdot K)$, with $K$ as the sum of the individual method complexity $O(V^2 + V^2 + V^2 + V)$, which leads to $O(V^3)$.

### 4.2. Determination of spatial-cognitive factor combinations

The UPRM predicts route choices based on the influencing factors of the underlying routing algorithms. Therefore, a calibration method must find influencing factor combinations that yield relevant pedestrian routes for a given scenario layout. We suggest a generic calibration approach in which these factors are determined by a test simulation comprising a finite set of test pedestrians, initialized with random factors. Then, the simulated routes are compared and clustered by an extended version of the turning angle metrics (Kneidl 2013). In each cluster, we group all routes that provide the same routing behavior for different factor combinations. Thus, we are able to find useful factors for a simulation scenario.

To find the suitable factor combination, the following steps must be executed: (1) run a test simulation with $n$ independent pedestrians with random factors; (2) calculate each routing path; (3) remove invalid routing paths; (4) calculate the turning angle metrics for the valid routing paths; (5) cluster the valid routing paths based on the metrics into sets; and (6) extract factors from the sets.

The first step of the generic calibration approach is the simulation. Here, the UPRM is used in a calibration mode, which generates random factor combinations for each test pedestrian. The pedestrians walk from a starting location to a single destination. After the simulation is finished, the vertices that each pedestrian visited during the simulation are put together to generate individual routing paths. Thus, the coordinates and order of the vertices are preserved. As a result, we obtain a set of routing paths that are associated with individual pedestrians. Fig. 4 (a) shows three example routing paths.

\[^2\text{There are several other approaches for clustering the routes, e.g., translating the routing paths pairwise into polygons and checking if obstacles reside within the combined polygon.}\]
Table 1. Turning angle calculations example for clustering using the example routes of Fig. 4. Here, we apply a threshold of $\pi/4$. As a result, paths 1 and 2 are in the same cluster, and path 3 is in another cluster.

<table>
<thead>
<tr>
<th>compared paths</th>
<th>sub-path</th>
<th>$\sum_{x=0}^{v_{si}} t_{cw,i} - \sum_{x=0}^{v_{sj}} t_{cw,j}$</th>
<th>$\sum_{x=0}^{v_{si}} t_{ccw,i} - \sum_{x=0}^{v_{sj}} t_{ccw,j}$</th>
<th>$e_{ij}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 and 2</td>
<td>1 to 7</td>
<td>$[3.4 - 1.27]$</td>
<td>$-2.04 + 2.33$</td>
<td>2.42</td>
</tr>
<tr>
<td>1 and 3</td>
<td>1 to 7</td>
<td>$[3.4 - 0.96]$</td>
<td>$-2.04 + 2.01$</td>
<td>2.47</td>
</tr>
<tr>
<td>2 and 3</td>
<td>2 to 6</td>
<td>$[1.27 - 0.96]$</td>
<td>$-2.01 + 2.33$</td>
<td>0.63</td>
</tr>
</tbody>
</table>

In some cases, a routing path might not reach the destination\(^3\), has cycles, or is very long. Thus, we remove routing paths for which the last vertex does not align with the destination location, for which a vertex is visited twice, or for which the path length exceeds the size of the simulation scenario by a factor of at least two. Here, the simulation scenario size is defined as the longest side of the bounding box of the scenario.

The next step is to calculate the turning angle metric. This metric is based on changes in the orientation angles along the routing path. We suggest an approach that calculates the angles by processing the vertices in the sequence of visits for each routing path. We measure the orientation difference between the current and next vertex in relation to a zero degree walking path. Thus, the angle measurements are in the interval $[-\pi, \pi]$. Fig. 4 (a) shows the turning angle profiles of the three example routing paths, and Fig. 4 (b) shows a plot of the profiles.

Next, we cluster the routing paths based on sub-paths and the turning angle metrics. We compare all routes pairwise and find all minimal disjoint sub-paths for each pair. For each pair, clustering is performed by adding up the turning angles for each disjoint sub-path with respect to the angle orientation. The results are four sums – two for each path. To determine if these two routes provide the same routing behavior, the sums for each route is individually subtracted with respect to the turning orientations. Then, the absolute sums are added up, which leads to the total error $e$ – expressed by Eq. 10. Here, $s_{ij}$ are the disjoint sub-paths of routes $i$ and $j$ with $i \neq j$, $v$ are the vertices in $s$, $t_{cw}$ are the clockwise turning angles, and $t_{ccw}$ are the counter-clockwise turning angles.

$$
e_{ij} = \sum_{k=0}^{s_{ij}} \left( \left| \sum_{x=0}^{v_{si}} t_{cw,i} - \sum_{x=0}^{v_{sj}} t_{cw,j} \right| + \left| \sum_{x=0}^{v_{si}} t_{ccw,i} - \sum_{x=0}^{v_{sj}} t_{ccw,j} \right| \right) \quad (10)$$

If the absolute sum exceeds a threshold, the routes are not part of the same cluster. Every time a route is added to a cluster, it will not be evaluated again. Furthermore, the lower the threshold, the more individual routes may exist and the higher it is, the fewer routes are found. We successfully applied a threshold of $\pi/4$ to this simulation study. In the festival case study described in Sec. 5, we successfully applied a value of $\pi/18$; however, more research will have to be done to contrive a generic approach to determine the threshold.

Tab. 1 shows the turning angle measurement results for the three example routing paths in Fig. 4. The value of the threshold is highly dependent on the length of the routes.

Finally, the factor combinations must be found. Therefore, we select the pedestrian with the highest survey-based factors from each cluster\(^4\). The factor combinations of the

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\(^3\)In some cases, the factor combinations emphasize lower-knowledge routing behavior in such a way that simulated pedestrians will get lost. Because we did not integrate a spatial learning concept, these lost pedestrians cannot recover. We will address this topic in further research.

\(^4\)Using the highest survey-based factor combination will be beneficial for integrating the social-cognitive aspects later on.
selected pedestrians are the calibration inputs for the UPRM. Thus, each cluster provides a factor combination that generates a feasible route.

Using this calibration method, we found 18 feasible factor combinations for an artificial test scenario (Tab. 2). Fig. 5 shows the resulting routes based on the found factor combinations. This evaluation provides evidence that the proposed calibration method yields plausible and applicable combinations for any network-like scenario layout.

The worst-case algorithmic complexity of the calibration method is an important aspect in identifying the practical usability of the concept. The calibration method combines six steps with individual worst-case complexity: (1) test simulations, (2) calculate routing paths, (3) remove invalid paths, (4) turning angle metrics calculation, (5) cluster valid routes based on the metrics, and (6) extract factor set. In the following, \( N \) is the number of test pedestrians and \( V \) is the number of vertices of the graph of the scenario. The worst-case algorithmic complexity of (1) is \( O(V^3 \cdot N) \) and based on the complexity analysis of Sec. 4.1. The worst-case complexity of (2 - 4) is \( O(V \cdot N) \) and can be found by the number of test pedestrians and the worst-case length of a routing path from origin to destination, which is \( V \). The worst-case algorithmic complexity of (5) is \( O(V^2 \cdot N) \), which is based on the pairwise comparison \( V \cdot V \) of each the worst-case path with the length \( V \). The algorithm (6) selects a factor set for each pedestrian; thus, the algorithm’s complexity is \( O(N) \).

4.3. Social-cognitive modeling

The social UPRM includes the heuristic rules proposed in Sec. 3.3. Herding in routing cannot take place without individual wayfinding capabilities; thus, we include the social-cognitive term to the weight calculation of the spatial-cognitive term. This unifies both approaches. Eq. 11 gives the weight calculation for the UPRM, including the spatial- and social aspects. Here, the successor vertex \( j \) is chosen as the next vertex to visit if the weight \( w_j \) is minimal.

\[
  w_j = \Theta \cdot w_j^{\text{spatial}} + \Xi \cdot w_j^{\text{social}}
\]  

The first summand is the term of the right-hand side of Eq. 9. The parameters \( \Theta \) and \( \Xi \) model the influence trade-off between the social and spatial components of the model, analogous to the factors of the spatial-cognitive part of the UPRM. The parameters \( \Theta \) and \( \Xi \) model the influence trade-off between the social and spatial components of the model.
Table 2. Factor combinations found by the calibration method for the artificial scenario.

<table>
<thead>
<tr>
<th></th>
<th>ζ</th>
<th>η</th>
<th>κ</th>
<th>ψ</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>0.00</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>b</td>
<td>0.26</td>
<td>0.42</td>
<td>0.81</td>
<td>0.78</td>
</tr>
<tr>
<td>c</td>
<td>0.12</td>
<td>0.31</td>
<td>0.75</td>
<td>0.45</td>
</tr>
<tr>
<td>d</td>
<td>0.10</td>
<td>0.37</td>
<td>0.99</td>
<td>0.02</td>
</tr>
<tr>
<td>e</td>
<td>0.06</td>
<td>0.30</td>
<td>0.94</td>
<td>0.15</td>
</tr>
<tr>
<td>f</td>
<td>0.12</td>
<td>0.24</td>
<td>0.40</td>
<td>0.87</td>
</tr>
<tr>
<td>g</td>
<td>0.20</td>
<td>0.23</td>
<td>0.75</td>
<td>0.71</td>
</tr>
<tr>
<td>h</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>i</td>
<td>0.18</td>
<td>0.12</td>
<td>0.02</td>
<td>0.75</td>
</tr>
<tr>
<td>j</td>
<td>0.21</td>
<td>0.00</td>
<td>0.03</td>
<td>0.76</td>
</tr>
<tr>
<td>k</td>
<td>0.05</td>
<td>0.15</td>
<td>0.50</td>
<td>0.62</td>
</tr>
<tr>
<td>l</td>
<td>0.08</td>
<td>0.16</td>
<td>0.75</td>
<td>0.95</td>
</tr>
<tr>
<td>m</td>
<td>0.00</td>
<td>0.14</td>
<td>0.33</td>
<td>0.91</td>
</tr>
<tr>
<td>n</td>
<td>0.07</td>
<td>0.03</td>
<td>0.43</td>
<td>0.68</td>
</tr>
<tr>
<td>o</td>
<td>0.05</td>
<td>0.00</td>
<td>0.99</td>
<td>0.67</td>
</tr>
<tr>
<td>p</td>
<td>0.31</td>
<td>0.01</td>
<td>0.57</td>
<td>0.73</td>
</tr>
<tr>
<td>q</td>
<td>0.24</td>
<td>0.00</td>
<td>1.00</td>
<td>0.69</td>
</tr>
<tr>
<td>r</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

and Ξ are deduced based on factor combinations of the spatial-cognitive part of the model, i.e., ζ, η, κ, and ψ. As explained above, ζ and η model the strength of the environmental knowledge (allocentric strategies). If the parameters are close to one, the pedestrian has a profound knowledge of the route network. These parameters provide important assumptions to find values for Θ and Ξ. Humans tend to copy other people's behavior if they feel they know less than others (Frith and Frith 2012). Therefore, we assume that the parameter Θ can be calculated based on the relative magnitude of ζ and η compared to κ and ψ. Consequently, we expect that there is an increase in copying behavior if Θ approaches zero. Naturally, we assume that Ξ = Θ − 1. Our approach to calculate the parameters is as follows:

\[
Θ = (ζ + η + χ) / (ζ + η + κ + ψ + χ) \tag{12}
\]

We emphasize the spatial-cognitive behavior by adding a lower boundary of χ to the term. This is mandatory to enable pedestrians to behave in an autonomous manner, even if ζ and η are near zero. The value of χ is in range [0, ∞]. We found that the range of [1.0, 3.0] provides a stable basis for autonomous routing that does not neglect herding behavior. Note that reducing χ to less than one may serve as a basis for pure herding simulations.

The second term of Eq. 11 is based on the weight calculation of the ACO and the FP methods.

\[
w_{j}^{social} = Λ \cdot w_{j}^{ACO} / m + (1 - Υ \cdot w_{j}^{FP} / \max (w_{j}^{FP})) \tag{13}
\]

The ACO and FP methods contribute to the calculation similar to the GBH and SALL methods. Thus, the weights of all successor vertices j of the current vertex i are evaluated individually for each method. Furthermore, the results are normalized in consideration of the maximal local weight of the neighboring vertices j for the FP method and the upper limit m for the ACO method.

The parameters Λ and Υ describe the influences of the herding rules within the social contribution of the model. In Sec. 5.2, we present a simulation study in which we evaluate the impact of herding behavior on simulations.
5. Case studies

To prove the suitability of our approach and the properness of our modeling assumptions, we present two real-life case studies. The first case study discussed here is an annual music festival in the vicinity of Munich, Germany. In this regard, we captured and compared GPS tracks of the on-foot arrival of the festival visitors with the results of the UPRM-based simulation. First, we present a validation approach regarding only the spatial-cognitive aspects. Then, we evaluate simulations that implement the social-cognitive extension of the model to show that the method yields promising results. The second case study is a wayfinding experiment with students in the inner city of Munich. Here, we show that the UPRM can be applied to complex and large-scale scenarios and that the UPRM is quite robust regarding an increase of graph complexity.

5.1. Validation of spatial aspects

We applied the UPRM to a music festival case study. Most of the festival visitors traveled towards the festival venue via subway. The subway trains arrived at the station near the festival venue every 20 minutes. After leaving the public transport station, the visitors walked to the festival venue on walkways and streets that were closed to car traffic. We captured the routing behavior of approximately 700 of 5000 festival visitors in 71 GPS measurements. Figs. 6 (a - f) show the complete set of routes chosen by the visitors.

Figure 5. (a - r) show routes created by the UPRM based on Tab. 2 for the artificial simulation scenario. All routes start at the top-left and end at the bottom-right. (s) shows all routes, and (t) represents the underlying graph used (Kneidl, Borrmann, and Hartmann 2012).
Figure 6. (a - f) show the measured walking routes of the festival visitors $A$ to $F$. (g - l) show the simulated walking routes $A$ to $F$. All routes start at the bottom and end at the top.

Based on the GPS measurements, we can validate the spatial-cognitive aspects of the model by comparing the real routes to the simulated route predictions of the UPRM.

Our validation process is as follows: (1) generate a graph for the scenario layout; (2) calibrate the model as described in Sec. 4.2; (3) simulate the travelers' route choices; and (4) compare the simulation results to the real data.

We apply an extended version of the graph generation method of Kneidl, Borrmann, and Hartmann (2012). For the algorithm, we set parameter $\alpha_{cone}$ to $24^\circ$ and the corner distance to 2.3 m. This parameter set is highly promising for city-like scenarios in which pedestrians can use the streets for walking. Our extension of the algorithm improves the edge generation of the graph generation model by first connecting the vertices that are closest to each other. Thus, the graph is recursively spanned considering the smallest distance between all vertices. This approach improves the edge distribution between vertices.

Tab. 3 shows the seven different factor combinations yielded by our calibration applying a tolerance of $\pi/6$. Compared to the results of Kielar et al. (2015), we forecasted an additional walking route due to an improvement of the underlying routing graph. The factor combination revealed that routes $F$ and $C$ are mostly used if the visitors have no local knowledge of the area. Routes $A$, $B$ and $D$ are used if few knowledge is present. Finally, route $E$ is associated with medium to good knowledge. As visualized in Figs. 6 (g - k), the simulation results show that the UPRM correctly predicted the route choices of routes $A$ to $F$. As discussed in Sec. 4.2, it is important to understand the distribution of factor combinations to assign the factors to simulated pedestrians. For this purpose, we used data from a questionnaire that provides information regarding the visitors local knowledge. Details about the usage and the questionnaire are provided in Sec. 5.2.

The model predicted an additional route $G$, which is an intermediate variation of routes $A$ and $F$ as well as the shortest path to the destination (Fig. 7). Nonetheless, the route is still realistic - but it might not have been measured due to incomplete coverage of the GPS measurements.
Table 3. Factor combinations found by the calibration method for the case study.

<table>
<thead>
<tr>
<th></th>
<th>ζ</th>
<th>η</th>
<th>κ</th>
<th>ψ</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.13</td>
<td>0.09</td>
<td>0.29</td>
<td>0.98</td>
</tr>
<tr>
<td>B</td>
<td>0.08</td>
<td>0.10</td>
<td>0.96</td>
<td>0.86</td>
</tr>
<tr>
<td>C</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
<td>0.00</td>
</tr>
<tr>
<td>D</td>
<td>0.25</td>
<td>0.00</td>
<td>0.88</td>
<td>0.77</td>
</tr>
<tr>
<td>E</td>
<td>0.96</td>
<td>0.99</td>
<td>0.95</td>
<td>0.80</td>
</tr>
<tr>
<td>F</td>
<td>0.02</td>
<td>0.02</td>
<td>0.56</td>
<td>0.15</td>
</tr>
<tr>
<td>G</td>
<td>0.98</td>
<td>0.68</td>
<td>0.99</td>
<td>0.96</td>
</tr>
</tbody>
</table>

5.2. Simulation study of social aspects

The spatial-cognitive part of the UPRM anticipates the routes used by the festival visitors in the case study (Sec. 5.1). However, it is not possible to predict the distribution of pedestrians who take different routes. We hypothesize that the social-cognitive components of the complete UPRM will provide an approach to predict the route usage distribution. Thus, we apply reasonable parameters for Λ, Υ, and χ to show that the simulation results comply with the measured data regarding route usage. Fig. 8 shows the routes chosen by the festival visitors upon arrival, as well as the percentages of route choice. The data was retrieved from the GPS measurements. Prior to running the social-cognitive simulations, we had to calibrate the ACO and FP models. In addition, an initial factor combination distribution for the spatial model aspects had to be found.

Fig. 9 shows the measured velocity distribution of the visitors walking to the festival. To obtain the velocity, we installed a camera at the end-point of the GPS tracking areas and used the video material for manual velocity determination of individual pedestrians (Biedermann et al. 2015). The distribution is used as a direct input parameter for the FP method. Thus, the simulation assigned a free flow velocity, which is drawn from the distribution to each simulated pedestrian.

Then, we had to calibrate the parameter of the ACO method. Here, the upper limit m of pedestrians and the decay rate ζ must be found by utilizing the GPS data. We extracted the parameter by analyzing pedestrian behavior at the split junction, which is shown in Fig. 8. The GPS data revealed two conditions under which multiple pedestrian groups chose to walk northwards or eastwards in a herd-like manner. Tab. 4 shows the data used to find the ACO parameter. Generally, if the number of pedestrians in a crowd walking
Figure 8. Routes the visitors chose to walk to the festival (A - F) and route usage percentages. The figure indicates the starting point and the end point of the GPS measurements as well as the main split junction.

Figure 9. Measured velocity distribution of the visitors walking to the festival venue.

to the venue exceeded 25, the groups always chose the same walking direction at the split junction. This effect is lost if the time gap between pedestrian groups approaching the venue exceeds approximately ten minutes. This duration is clearly related to the perception of the follow-up groups, as they could not see the predecessor groups after this time period. If the number of pedestrians was less than 25, the pedestrians in the group chose the northward, eastward, or both directions. Therefore, the upper limit parameter $m$ was set to 25 and the linear decay rate $\varsigma$ was set to 0.0417, which enables the pheromone level to drop to zero within ten minutes.

Finally, we identified the initial relative amount of pedestrians walking with the spatial-cognitive factor combinations. We matched the factor combinations provided by the calibration (see Sec. 5.1) with the data of a festival visitor questionnaire regarding local knowledge. The questionnaire is helpful to determine the distribution of initial factor combinations. Tab. 5 shows the factor mapping we used for the simulations. Note that the initial factor distribution does not provide the real route usages of the festival visitors, but a rough initial estimation that is used as the seed for herding effects.

Tab. 6 provides the simulation results of herding behavior for the case study with different parameter values for $\Lambda$, $\Upsilon$, and $\chi$. Here, a single simulation represents a situation in which pedestrians leave the subway and walk to the festival venue. We estimated the pedestrian load of the suburban trains arriving at the stations during the festival day.
Table 4. Aggregated GPS measurement data used to find the ACO parameter. The $\Delta t$ value describes the relative time gap between the measurements of the current and the previous row. If the time delta for GPS measurements was less than ten minutes, the GPS measurements were merged. The size of the crowds describes the number of pedestrians in a merged GPS measurement. The direction indicates whether the crowd walked northwards, eastwards, or in both directions at the split junction shown in Fig. 8.

<table>
<thead>
<tr>
<th>$\Delta t$ hh:mm</th>
<th>crowd size</th>
<th>split junction direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>-</td>
<td>9</td>
<td>north</td>
</tr>
<tr>
<td>01:17</td>
<td>10</td>
<td>north</td>
</tr>
<tr>
<td>00:19</td>
<td>21</td>
<td>both</td>
</tr>
<tr>
<td>00:17</td>
<td>23</td>
<td>both</td>
</tr>
<tr>
<td>00:15</td>
<td>58</td>
<td>north</td>
</tr>
<tr>
<td>00:16</td>
<td>52</td>
<td>north</td>
</tr>
<tr>
<td>00:18</td>
<td>7</td>
<td>north</td>
</tr>
<tr>
<td>00:20</td>
<td>26</td>
<td>north</td>
</tr>
<tr>
<td>00:17</td>
<td>71</td>
<td>north</td>
</tr>
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<td>00:16</td>
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<td>00:13</td>
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<td>00:13</td>
<td>53</td>
<td>north</td>
</tr>
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<tr>
<td>00:11</td>
<td>17</td>
<td>east</td>
</tr>
<tr>
<td>00:14</td>
<td>18</td>
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<td>north</td>
</tr>
<tr>
<td>00:24</td>
<td>3</td>
<td>north</td>
</tr>
</tbody>
</table>

Table 5. Mapping of the local knowledge of visitors to the initial factor usage probability distribution. If multiple routes are mapped to a single or multiple questionnaire answers, the probability is equally summed and distributed between the routes. We merged and split the route usage with regards to the probabilities based on the sum of the high knowledge factor combinations of $\zeta$ and $\eta$. The questionnaire data was provided by Prof. Annette Spellerberg and her research team Urban Sociology, University of Kaiserslautern.

<table>
<thead>
<tr>
<th>Local knowledge</th>
<th>%</th>
<th>Route</th>
<th>high knowledge factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
<td>33.1%</td>
<td>$C &amp; F$</td>
<td>0.02 ± 0.02</td>
</tr>
<tr>
<td>Little</td>
<td>15.6%</td>
<td>$A &amp; B &amp; D$</td>
<td>0.217 ± 0.029</td>
</tr>
<tr>
<td>Some</td>
<td>20.4%</td>
<td>$A &amp; B &amp; D$</td>
<td>0.217 ± 0.029</td>
</tr>
<tr>
<td>Good</td>
<td>12.7%</td>
<td>$E$</td>
<td>1.94</td>
</tr>
<tr>
<td>High</td>
<td>18.2%</td>
<td>$E$</td>
<td>1.94</td>
</tr>
</tbody>
</table>

using the Oppilatio method (Biedermann, Kielar, and Borrmann 2015). We found that - after the arrival of a subway train - an average number of 218 people left the subway station to walk to the venue, with a standard deviation of 128. This data was used to estimate the number of pedestrians for each simulation.

The herding results are shown in Tab. 6 are quite close to the measured data. Route $E$ was dominant in all simulations and the general herding tendency was reproduced. The best results with respect to the absolute and mean percentage error 8.08% and 1.35% are found for $\Lambda = 0.4$, $\Upsilon = 0.6$, and $\chi = 2$. For the sake of comparison with the spatial-cognitive aspects, we included the spatial component of the UPRM without herding behavior in Tab. 6. The route usage ratios of this line obviously converge against the initial factor distribution and exhibit the worst error profile.

In summary, the route usage percentages for the herding approach reveal that our
Table 6. Simulation results of route usage for routes (A - F) for the spatial- and social-cognitive routing simulation. All values are given in percentage, except parameters $\Lambda$, $\Upsilon$, and $\chi$. The number of executed simulations was 30 for each column. The last column shows the real route usage and the second to last column shows the result data for 30 simulations without herding behavior. The last row gives the mean absolute error in percentage and the second to last row gives the cumulated absolute error in percentage for each column.

<table>
<thead>
<tr>
<th>$\Lambda$</th>
<th>0.4</th>
<th>0.5</th>
<th>0.6</th>
<th>0.4</th>
<th>0.5</th>
<th>0.6</th>
<th>0.4</th>
<th>0.5</th>
<th>0.6</th>
<th>0.4</th>
<th>0.5</th>
<th>0.6</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Upsilon$</td>
<td>0.6</td>
<td>0.5</td>
<td>0.4</td>
<td>0.6</td>
<td>0.5</td>
<td>0.4</td>
<td>0.6</td>
<td>0.5</td>
<td>0.4</td>
<td>0.6</td>
<td>0.5</td>
<td>0.4</td>
</tr>
<tr>
<td>$\chi$</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| $\Lambda$ | 1.76 | 0.25 | 0.33 | 0.41 | 1.24 | 1.31 | 0.76 | 0.64 | 12.41 | 2 |
| $\Upsilon$ | 5.94 | 0.60 | 0.95 | 1.73 | 0.71 | 4.42 | 2.39 | 1.51 | 2.48 |
| $\chi$ | 0.24 | 1.75 | 1.67 | 1.07 | 1.59 | 0.76 | 0.69 | 1.24 | 15.41 |

| $\sigma_B$ | 4.74 | 4.92 | 2.69 | 11.79 | 13.41 | 5.24 | 12.08 | 15.76 | 14.59 | 1.60 |
| $\Delta_B$ | 7.69 | 7.93 | 8.50 | 0.34 | 5.88 | 19.14 | 9.43 | 3.95 | 1.73 |

| $C$ | 1.33 | 0.41 | 0.22 | 3.23 | 1.33 | 0.52 | 2.81 | 1.36 | 5.16 | 16.00 | 5 |
| $\sigma_C$ | 0.00 | 0.98 | 0.52 | 6.14 | 2.82 | 1.11 | 2.78 | 2.62 | 3.08 | 2.21 |
| $\Delta_C$ | 0.00 | 4.59 | 4.78 | 1.77 | 3.67 | 4.48 | 2.19 | 3.64 | 0.16 | 11.00 |

| $D$ | 2.58 | 0.92 | 0.62 | 6.64 | 3.97 | 2.11 | 10.30 | 8.91 | 5.16 | 11.88 | 7 |
| $\sigma_D$ | 3.14 | 1.19 | 1.03 | 2.94 | 3.53 | 2.68 | 2.99 | 2.81 | 3.08 | 1.67 |
| $\Delta_D$ | 4.42 | 6.08 | 6.38 | 0.36 | 3.03 | 4.89 | 3.30 | 1.91 | 1.84 | 4.88 |

| $E$ | 88.71 | 94.51 | 96.56 | 71.92 | 79.02 | 89.28 | 42.23 | 57.43 | 66.71 | 31.26 | 70 |
| $\sigma_E$ | 15.22 | 9.69 | 4.01 | 18.37 | 23.25 | 12.05 | 12.31 | 19.63 | 18.15 | 2.85 |
| $\Delta_E$ | 18.71 | 24.51 | 26.56 | 1.92 | 9.02 | 19.28 | 27.77 | 12.57 | 3.29 | 38.74 |

| $F$ | 3.31 | 1.85 | 0.77 | 7.61 | 6.56 | 2.73 | 14.21 | 12.11 | 8.39 | 16.73 | 5 |
| $\sigma_F$ | 7.11 | 5.00 | 0.92 | 10.21 | 7.93 | 3.62 | 8.11 | 7.82 | 8.67 | 2.56 |
| $\Delta_F$ | 1.69 | 3.15 | 4.23 | 2.61 | 1.56 | 2.27 | 9.21 | 7.11 | 3.39 | 11.73 |

| $\Delta_{sum}$ | 36.42 | 48.02 | 52.12 | 8.08 | 20.16 | 37.56 | 62.30 | 35.91 | 13.99 | 78.49 |
| $\Delta_{sum}$ | 6.07 | 8.00 | 8.69 | 1.35 | 3.36 | 6.26 | 10.38 | 5.99 | 2.33 | 13.08 |

The method provides realistic herding behavior in routing because the simulation results emphasize route $E$ in all cases. This is especially true because the mean percentage error of all herding-based simulations with regards to the real data is 5.83%. In comparison, the simulation results without herding provide a mean percentage error of 13.08%.

### 5.3. City district scale simulation study

The second case study is based on the data of a wayfinding experiment by Kneidl (2013). In the original study, 31 small groups comprising 91 students had to navigate from an origin district to a destination area in the city center of Munich. The small groups of two up to five people started independently and with a delay between the starts at one of four different starting positions. The goal was to reach a destination area by walking without the help of utilities on public routes outside of buildings. Before the experiment, the participants had the opportunity to take a look at the map of Munich to orientate themselves. During the experiment, the students used hand written protocols to record their walking paths. We used the data of the experiment and compared the data to simulations results of the UPRM in order to show that the UPRM can be applied to large-scale environments with reasonable accurate results. Thus, we run a calibration simulation of the spatial-cognitive wayfinding behavior and compared the results to the real routes the participant chose.

Fig. 10 depicts the simulation and experiment area and provides information about the correctly predicted street usage (pink routes) and the incorrectly predicted street usage (orange and blue routes). The UPRM forecast the overall wayfinding behavior of the participants of the study correctly; however, the model could not predict all route choices. We quantify the degree of correct predictions by the ratio of the number of
correctly predicted route choices to the overall number of route choices. Hence, if the UPRM misses to forecast a route choice (blue circle) or selects a route incorrectly (orange circle), the ratio decreases. Similarly, if the UPRM choose a route at decision point that was chosen by a participant group (empty circle), the ratio increases. The number of correct route choice predictions is 77 (empty circles) and the number of incorrectly predicted route choices is 25 (10 orange and 15 blue circles). Therefore, the number of correctly predicted route choices is 77 out of \(25 + 77\) = 102, which defines a ratio of 75.49\%. However, the routing graph of this large-scale study comprises 2366 vertices and 14912 edges. Hence, the number of vertices increased up to 3943.3\% and the number of edges increased up to 4142.22\% in comparison to the 60 vertices and 360 edges of the case study of Sec. 5.2. Note that both graphs were generated by the method of Kneidl, Borrmann, and Hartmann (2012). We conclude that the UPRM is quite robust and provides reasonably accurate results for scenarios with high complex graphs.

We are confident that the inaccuracies of the UPRM in the large-scale simulation study can be explained by the fact that some participants temporarily lost orientation during the experiment. Thus, the participants started to walk towards the wrong direction. This is shown by many paths that deviated in regards to the beeline directions to the destination, which correspond to most of the blue routes in Fig. 10. The deviations contradict the initial precondition of the UPRM, which is that the pedestrian has an idea of where the goal location is. Therefore, the experiment provides important pointers for further developments of the UPRM. Nonetheless, the model is capable of simulating wayfinding in city district scale and still provides reasonable prediction power.

6. Discussion

Our approach to unify multiple pedestrian route planning methods yields realistic and accurate results for network environments. The results could only be achieved by integrating well-studied pedestrian wayfinding models (Kneidl 2013) into a combined model. Furthermore, the initial approach of combining the algorithms in a linear fashion provided positive results, as shown in the case studies in Sec. 5. Due to the generic underpinning of the model, other route planning aspects can be easily integrated into the model by adding a term and a factor to the corresponding social or spatial terms. Nonetheless, the UPRM poses several new research opportunities and challenges for the future:

First, the model builds upon routing graphs. Thus, the graph generation is the crucial predecessor step before the model can be applied. If the generation method provides insufficient graphs, the model may yield unreasonable results. Here, the properties of the underlying graphs and their application as cognitive maps require further research. We will attempt to find a common set of properties for graphs that can be used as a guideline for generating high-quality routing graphs. In Sec. 5.1, the model forecasts the route choices of pedestrians quite well; however, the model predicted an additional route that we had not measured. We assume that the revealed uncertainty in finding an additional route is based on a non-optimal routing-graph. We used an extended version of the graph-generation method of Kneidl, Borrmann, and Hartmann (2012) for the case study scenario; however, it may be necessary to include further or other graph generation methods to find additional high-quality routing networks.

Second, the factor combinations are static in our approach. However, people learn and remember details about their surroundings during navigation (Wiener, Büchner, and Hölscher 2009; Hölscher, Tenbrink, and Wiener 2011). These aspects continuously shift the factors towards a profound knowledge combination. Also, people may forget spatial information; thus, the factors may shift toward a less profound knowledge combination.
All aspects, i.e., learning, rehearsal, and forgetting spatial properties of environments, should be included in the model. In addition, people are often only familiar with parts of the spatial environment. Taking that into account, we will extend the model in such a way that the factor combination changes instantaneously if a pedestrian enters another environment district she/he has a different knowledge base of. This is also indicated in the city scale case study. Here, the participants lost orientation and deviated strongly from a beeline direction towards the destination.

Third, we presented a calibration method for the spatial-cognitive component of the model but could not find a calibration approach for the social-cognitive aspects. In future, we will address this issue in order to reduce the relevant assumptions for applying the UPRM including the social-cognitive components. Nonetheless, our generic methodology that includes the calibration approach allows researchers to apply the model to different use cases.
Fourth, the UPRM finds multiple routes pedestrians take to approach a certain location. However, there are graph-based algorithms that also find multiple routes, e.g. the 'k-shortest path method' (Yen 1971). We are confident that these methods will create many routes that pedestrian may never take in reality. Applying this discrepancy as a benchmark for pedestrian routing algorithms is a promising further research aspect for the UPRM.

Fifth, the UPRM is designed to simulate realistic pedestrian behavior in network environments. In open environments, however - e.g. squares - the model might not yield appropriate results. This is due to the fact that the goal location is always visible in open environments and the knowledge approach can be superfluous. Nonetheless, we suspect with an adjustment of the Eq. 12 and an optimization of the underlying graph structure, the UPRM can handle open space scenarios.

Finally, routing in social groups is investigated by cognitive scientists. Thus, another promising next step to develop the routing model would be to include social group wayfinding and orientation loss during navigation as additional factors of the UPRM.

7. Conclusions

In contemporary research into computational pedestrian wayfinding models for cities and buildings, there is still no comprehensive concept that includes a multitude of different aspects in microscopic pedestrian route planning. Computational simulations of pedestrian route planning are complex because spatial- and social-cognitive aspects determine and influence human wayfinding behavior.

In this paper, we presented the Unified Pedestrian Routing Model (UPRM), which combines spatial- and social-cognitive components in a single methodology for pedestrian wayfinding behavior simulations. The individual aspects are modeled via graph-based route planning algorithms and are mathematically combined into a single routing method. The proposed model includes the spatial-cognitive aspects of route- and survey-based wayfinding behavior and, more importantly, mixed variants of these routing strategies. In addition, we modeled the social-cognitive aspects of herding behavior. We understand herding as an influence on route choice, originating from predecessor pedestrians that are in sight, not as group influences in the way of social group cohesiveness or queuing behavior.

By utilizing pedestrian simulations, we were able to show that the proposed UPRM can model a very large set of realistic routes. We also presented a calibration method for the spatial-cognitive parts of the UPRM. In addition, we validated the spatial-cognitive aspects of the UPRM using a festival case study. We were able to forecast all of the visitor arrival routes in the study. Therefore, our approach of combining existing graph-based pedestrian routing methods to simulate a more realistic routing behavior was successful. We also performed a simulation study for the herding behavior aspects of the UPRM. The results show that we can improve the overall prediction of the visitor’s route usage from a mean error of 13.08% without herding effects to a mean error of 1.35% with herding. This implies that our concept for integrating social-cognitive phenomena of herding is beneficial. The last case study applies the UPRM to data of a city district scale wayfinding experiment. We showed that the model can predict 75.49% of the routes choices of the participants and that the model can be applied complex large scale environments.

However, the model operates on graphs. Thus, if the underlying routing graph generation method yields low-quality graphs, the proposed model cannot operate properly. Further research must focus on understanding the underlying properties of high-quality routing graphs. Also, several other research questions arose. For example, we will work
on an effective calibration method for the social-cognitive parts of the proposed UPRM. The developed routing model can be applied to all pedestrian simulations that use integrative graph-based routing models for cities and buildings. Thus, our contributions will improve pedestrian simulation concepts by providing a pedestrian wayfinding model that satisfies the requirements of a realistic and versatile routing behavior.

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