Modeling pedestrians' interest in locations: A concept to improve simulations of pedestrian destination choice

Peter M. Kielar[a,*], André Borrmann[a]

[a] *Technische Universität München, Chair of Computational Modeling and Simulation, Arcissstraße 21, 80333 München, Germany*

Abstract

Large environments that are designed for travel, leisure, and for everyday life – such as transport hubs, amusement parks, and shopping centers – feature different locations that are frequently visited by pedestrians. Each visit is evoked by one's motivation to engage in some kind of activity at a certain location. By means of modeling the pedestrians' interests in locations with the aid of computer simulations, it is possible to forecast the occupancy at locations by utilizing sophisticated pedestrian destination choice models. In the field of pedestrian dynamics research, location preference modeling is not common, but it is all the more rare to include a psychological grounding into such choice models. Here we show that our psychologically inspired and mathematically defined model to describe pedestrians' interests in locations is able to improve the exactness of pedestrian destination choice models. The interest function model is based on the psychological concept of goal-related memory accessibility and on fundamental coherences found in pedestrian-related data that is measurable at locations. We validated the interest function model and our results provide evidence that our approach improves the simulation fidelity regarding occupancy forecasting. Because the interest concept is designed as a framework that can be coupled to existing microscopic pedestrian simulators, it can be used in most pedestrian destination choice models to describe pedestrian visiting preferences. Consequently, the reliability of the occupancy predictions of pedestrian simulations can be enhanced by integrating the interest function model into choices models.

Keywords: pedestrian dynamics, pedestrian behavior simulation, destination choice, occupancy, goal-related memory accessibility

*Corresponding author. Tel: +49 89 289-23062; Fax: +49 89 289-25051

Email addresses: `peter.kielar@tum.de` (Peter M. Kielar), `andre.borrmann@tum.de` (André Borrmann)

URL: `https://www.cms.bgu.tum.de/en/team/peter-kielar` (Peter M. Kielar)

1. Introduction

Pedestrian simulations aim to predict pedestrian movement behavior in different environments. Decision makers can identify dangerous situations and increase pedestrian safety by evaluating the prediction models' simulation results. We describe these results as macroscopic pedestrian performance indicators. An important indicator is the pedestrian flow that describes the throughput of pedestrians in time and space between two locations [58], e.g., a route connected by two junctions. The pedestrian flow decreases with an increasing number of pedestrians [52]. Additionally, the flow changes if the geometric layout of the surroundings impedes walking [42]. Another important indicator is to be seen in high pedestrian densities [50]. A well-known tragic example in which high pedestrian densities played a key factor is the Love Parade disaster [28]. In contrast to the macroscopic indicators, microscopic indicators account for people's walking properties such as the position, the direction and the velocity. Hence, it is the microscopic pedestrian walking behavior that leads to macroscopic pedestrian-related performance indicators. Therefore, microscopic pedestrian computer simulations are used to forecast macroscopic performance indicators [1, 16, 36, 56, 60].

In our work, we focus on a specific macroscopic factor: the number of visitors at a location over time, in other words, the location's occupancy. This time dependent value ultimately describes the pedestrians' visiting patterns at a location, which is a macroscopic indicator for capacity caps and safety issues [50, 57]. The occupancy emerges due to microscopic behavior of pedestrians comprising repeated stays at locations and travel among locations. Hence, chains of destination choices describe a complex visiting process. In the literature, this process is referred to as *trip chain* [46], *multipurpose trip* [15], *plan* [25], or *spatial sequential choice* [23]. In pedestrian dynamics, the selection of the next location to visit is defined as *strategic behavior* [30] and is also known as *destination choice* or *goal selection*. In general, a pedestrian selects a destination to visit because he/she prefers to engage in an activity on offer at that location over another activity. Thus, choice of destination includes a range of motivational properties, which guide and drive pedestrian behavior.

One issue in contemporary pedestrian dynamics research is that there are only very few models of pedestrian destination choice that takes psychological factors into account. Because modeling pedestrian behavior is essentially about modeling human behavior, we believe that introducing a psychologically grounded methodology to model pedestrians' location preferences will improve destination choice models. We approach this research gap by proposing a new framework to model pedestrians' interests in form of a mathematical function. The theoretical groundings of the interest function model are the psychological concept of goal-related memory accessibility and the fundamental coherences found in measurements of pedestrians visiting locations. Drawing on computer simulations, we can show that the interest function model is valid as stand-alone concept. Additionally, we are able to improve an existing task queuing destination choice model [53] with the interest function model and provide evidence that the approach outperforms the widely used origin-destination matrix approach on a multi-location simulation scenario. The results provide evidence that applying the interest function model improves pedestrian occupancy forecasts by improving destination choice simulations.

The remainder of this paper is structured as follows. In Section 2, we present contemporary strategic behavioral modeling approaches and related work. Section 3 begins with a recapitulation of the necessary psychological groundings, followed by a mathematical description of the interest functions framework. Additionally, the regeneration of the occupancy at a location is explained. The validation of the interest function framework for a single location concludes Section 3. In Section 4, we show how to integrate the model into existing microscopic models of pedestrian behavior. Furthermore, we present and evaluate results of interest-based pedestrian computer simulations for multiple locations. The paper closes with a discussion about challenges in Section 5 and concluding remarks in Section 6.

2. Related work

The concept of categorizing pedestrian behaviors as strategic, tactical, and operational behavior is an accepted approach in pedestrian dynamics [14, 30, 31]. Strategic behavior describes destination choice and models sequencing activities – while tactical models depict the pedestrians' navigation behavior by defining an approximated walking route that starts at the pedestrian's current position and ends at a certain destination. Operational models relate to the manner of walking to the next visible intermediate navigation node, adjoining the walking route and interacting with other pedestrians and obstacles along the way.

The history of strategic pedestrian behavioral research is well summarized by Timmermans et al. [55]. Early approaches to model strategic behavior were driven by attempts to assess the efficiency of shopping malls [15]. However, many strategic pedestrian behavioral models are application-independent, and the most widely used generic approach is the origin-destination matrix (OD matrix) concept. An OD matrix is a Markov chain model [55] that describes the probability of visiting a destination if a pedestrian is at a specific origin location. The model is time-invariant and quite easy to apply. Nonetheless, the OD matrix approach is difficult to apply in larger application scenarios [14] and is still being studied [20, 34]. In addition, more sophisticated approaches have been developed in recent years [16, 19, 25, 30]. The research highly related to our work are the need-based approach of Arentze and Timmermans [7] and the potential attractivity measure concept of Danalet et al. [17]. Both models are original approaches, but based on other grounds than those of the interest function model. Hence, we provide a new perspective to this branch of research.

In general, psychology-based concepts receive increasing attention in pedestrian dynamics research. Approaches considering human psychology and cognitive abilities are already established in operational models [32, 45, 47] and tactical models [10, 37, 38]. Even if rare, there are examples for psychologically enhanced strategic pedestrian behavioral models [35, 41, 59, 61].

The development of computationally implementable models regarding human cognition, behavior, and decision making is nowadays highly advanced [11, 29, 54]. For example, the adaptive control of thought (ACT) by Anderson [3] is widely used in different variations and has been continuously improved. Balke and Gilbert [8] presented an in-depth survey about models and architectures of human decision making for social simulations. One of the main drawbacks of many of these highly advanced models and architectures is that they are not designed for strategic pedestrian behavior modeling. However, there are exceptions – such as work of Pelechano et al. [48] and Wijermans et al. [61].

Despite different approaches and modeling paradigms for strategic behavior, a surprising void was identified in most strategic models. Often, the destination choice is modeled based on a change in motivation, desire, urge, drive, or will – but there are hardly any implementable mathematical functions presented to describe these factors. If such functions are defined, they are mostly not based on a profound psychological grounding or, conversely, the concepts are not designed for applications in the scope of pedestrian dynamics.

3. The interest function model

In this Section, we first elucidate the theoretical groundings of the interest function model. Afterwards, we describe the mathematical framework of the interest function model for a single location[1]. With this background, we will show how the interest functions of multiple pedestrians lead to the occupancy of a single location.

3.1. Psychological groundings

Here we clarify the interest function's psychological groundings, most importantly drawing on the work of Masicampo and Ambady [43]. They provide important findings regarding the interconnections of widespread interest and individuals' interests.

Anderson [4] describes that humans store knowledge conceptually; thus, information is stored and linked according to meaning and context in a propositional network. As a consequence of this theory, the process of recalling an item will also increase the probability of recalling other items that are associated [2, 4]. A possible example in our context might be that if an amusement park visitor is hungry, then he/she will be more aware of information related to restaurants, will remember a meal's taste, or a restaurant's location. Hence, the effectiveness of recalling information connected to hunger is enhanced. Nonetheless, a mathematical function to account for the recall probability has to be included. Anderson and Milson [5] and Anderson and Schooler [6] provide the so-called *need probability theory* according to which a sigmoid function is the best choice for a mathematical model of the recall probability (see Figure 1 (a)).

[1] We provide our pseudo-code of the framework in the Appendix.

The theory induces that if memory recall increases regarding items associated to a certain goal, the mental state of a person is more and more directed towards it. Förster et al. [22] provided evidence for this hypothesis and showed that if people are given goals, this will increase the accessibility of goal-related information. Thus, while pursuing a goal, a person will focus on goal-related information, leading to an increase of the recall-effect. Further, this effect will become all the more distinct the closer a person is to fulfilling the goal (or seems to be). If a goal is reached, it would be a burden for pursuing other goals if the active information connected to the fulfilled goal were to be kept – so the enhanced accessibility is discarded [21].

Masicampo and Ambady [43] connected the concepts of goal-related accessibility, need probability, and widespread interest. Based on – and in agreement with Anderson and Schooler [6] and Förster et al. [22], they argue that memory patterns describe a cognitive approach towards goals. These patterns are a good substitution and approximation for the peoples' interest in goals. This similarity allows them to describe goal-related interest and goal-related memory accessibility likewise as sigmoid functions. They also provided evidence for their hypothesis by analyzing Internet-based search trends, showing that a sigmoid pattern can be regenerated if the interests of many people in a single goal are accumulation. Hence, group interest is created by the individuals' interests and the widespread goal-related patterns follow the need-probability concept. A qualitative visualization of the concept is shown in Figure 1 (b). The important conceptual difference of our approach to the work of Masicampo and Ambady [43] is that they focused solely on public triggering events (e.g. elections or holidays), whereas this work's primary focus lies on triggering events concerning individuals (e.g. the need to satisfy hunger or interest in a shop window). Naturally, the internal triggering events of pedestrians are not synchronized like the public triggering events. Additionally, the goals we describe are physically approachable; thus, a goal is always directly associable to a location.

Based on the aforementioned findings of psychological research, the interest function is modeled as a sigmoid function. A sigmoid function can represent the cognitive approach to a goal, which is interpreted as the interest of a pedestrian in a location.

3.2. Model construction

An interest function is a non-continuous composition comprising a sigmoid function part and a linear function part. The sigmoid part models the increasing interest of a pedestrian in a goal at a location, and the linear fulfillment part describes the realization of that goal, including waiting times. The higher the magnitude of the function, the higher the probability of visiting a certain location. Therefore, the motivation of performing an activity associated to a location is directly connected to the magnitude of the interest function. Because it is common that pedestrians visit a location more than once, the interest concept integrates a repetition mechanism. Figure 2 (a) provides a qualitative description of an interest function and Figure 2 (b) an interest function repetition.

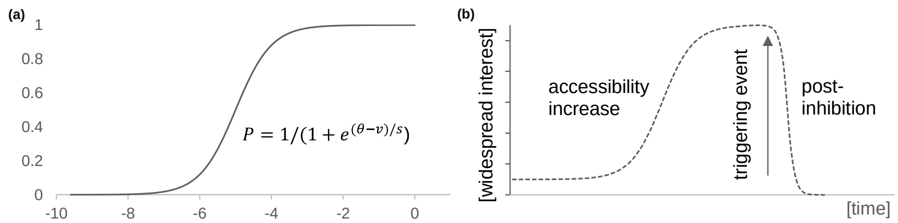

Figure 1:
(a) Example from Anderson and Milson [5] ($\theta = -5$ and $s = 0.5$). The abscissa describes the abstract concept of the need to remember and the ordinate represents the probability for recalling the memory.
(b) Generic example of the increasing widespread interest and inhibition in a goal before and after a triggering event [43]. The abscissa is a time scale and the ordinate is an interest scale.

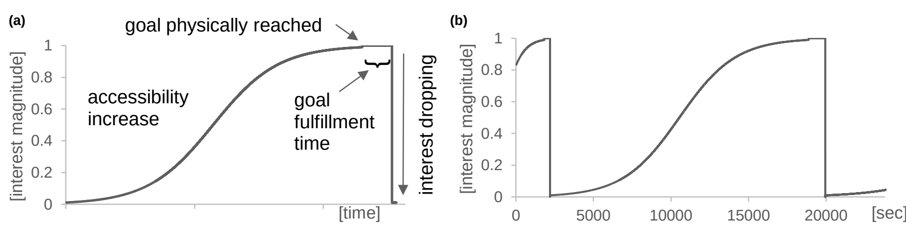

Figure 2:
(a) Qualitative description of the interest function. The abscissa is a time scale and the ordinate is an interest magnitude between zero (not interested) and one (interested).
(b) Example of a repetitive interest function. The abscissa represents the time in seconds and the ordinate accounts for an interest magnitude between zero (not interested) and one (interested).

The duration between the extreme values of a pedestrian being not interested and being very interested is unknown. To determine the unknown duration and to model the interest function, we use statistical field data that can be collected from pedestrians at a location. The data sources are the service time distribution μ of a location, the interarrival time distribution ν of a location, the number of measurements creating the interarrival time distribution $|\nu|$, and η, which comprises the number of pedestrians and the maximal number of inflowing pedestrians at a scenario. The interarrival time distribution indicates the duration between the successive arrivals of two pedestrians at a location. The service time distribution accounts for the time a pedestrian spends at a certain location; thus including the duration of waiting and engaging in the activity. The distributions' data is always measured in an observation time frame $[t_i, t_j]$ and at a location a.

Fundamental dependencies can be found in the data, which helps to define a mathematical function of the interest raising duration. A very prominent coherence is that the moments at which pedestrians appear at a location a is based on the interarrival time distribution ν of the location a and the maximal number of pedestrians η at the scenario. These fundamental dependencies are qualitatively described in Figure 3, but shown without borderline cases (e.g. capacity caps). Based on the fundamentals, the interest raising duration ω_{a,t_i,t_j} can be estimated. For that we use η_{a,t_i,t_j}, an interarrival time value ν_{a,t_i,t_j} that is drawn out of the interarrival time distribution, and a springing term sp_{a,t_i,t_j}, which compensates normalization of the interarrival distribution regarding a low or high number of visitors.

$$\omega_{a,t_i,t_j} = sp_{a,t_i,t_j} \cdot \eta_{a,t_i,t_j} \cdot \nu_{a,t_i,t_j} \tag{1}$$

The spring term is based on a polynomial function that includes η_{a,t_i,t_j} and the measured number of pedestrian interarrival times $|\nu_{a,t_i,t_j}|$.

$$k = \alpha / (\eta^h_{a,t_i,t_j} - (\eta_{a,t_i,t_j} \cdot \beta)^h) \tag{2}$$

$$sp_{a,t_i,t_j} = k \cdot (|\nu_{a,t_i,t_j}|^h - \eta^h_{a,t_i,t_j}) \tag{3}$$

The spring term introduces important constraints, e.g., if less interarrival data could be measured, ω_{a,t_i,t_j} goes towards infinity. The model constants α and β are calibrated by stepwise optimization (see Section 3.4). For the constant h we use the value -1.55, a number we found by preliminary simulation tests.

The next step is to model the interest repetition time span δ_{a,t_i,t_j} between two repetitive visits of a pedestrian. The repetition is described as the sum of the time ω_{a,t_i,t_j} until a pedestrian visits the location a and a service duration μ_{a,t_i,t_j}, which is drawn from the service time distribution.

$$\delta_{a,t_i,t_j} = \omega_{a,t_i,t_j} + \mu_{a,t_i,t_j} \tag{4}$$

The interest rises until a threshold is reached and then drops to a lower threshold after performing the activity. Afterwards, the interest rises gradually until the upper threshold is met again. The maximal interest threshold Ω_{mat} is set to 0.99 interest and the minimal interest threshold Ω_{mit} is set to 0.01. These thresholds are changeable model constants, which are based on the simulation time step discretization. Based on the previous equations, one can calculate the interest duration parameter ζ_{a,t_i,t_j} for reaching Ω_{mat} in ω_{a,t_i,t_j}. The parameter ζ_{a,t_i,t_j} changes for each repetition and each pedestrian due to changing values drawn from the underlying distribution.

$$\zeta_{a,t_i,t_j} = (\omega_{a,t_i,t_j}/2)/-ln(1/\Omega_{mat} - 1) \tag{5}$$

Finally, the rising phase of the interest function ψ for a repetition is:

$$\psi_{t,a,t_i,t_j} = (1 + e^{-t/\zeta_{a,t_i,t_j}})^{-1} \text{ for } t \in [-\omega_{a,t_i,t_j}/2; \omega_{a,t_i,t_j}/2] \tag{6}$$

The function ψ_{t,a,t_i,t_j} is valid for the phase of rising interest with $\Omega_{mit} \leq \psi_{t,a,t_i,t_j} \leq \Omega_{mat}$. After reaching Ω_{mat}, the fulfilling phase is valid:

$$\psi_{t,a,t_i,t_j} = x \text{ for } t \in]\omega_{a,t_i,t_j}/2; \delta_{a,t_i,t_j} - \omega_{a,t_i,t_j}/2] \tag{7}$$

The parameter x equals one if the interest function represents the visiting desire of a single pedestrian. Nonetheless, pedestrians often travel in groups and visit locations together. Examples of such continuous group cohesiveness regarding walking behavior are described in Bandini et al. [9] and Peters and Ennis [49]. The interest function can account for pedestrian groups if parameter x is changed according to the group size. Based on this extension, the function describes the homogenized and joint interest of a group of x members in a certain location.

In general, the function ψ_{t,a,t_i,t_j} describes a repetition of an interest phase. The transitions between the rising interest and the interest fulfillment phase are not explicitly modeled; thus, the phases change in an instant. This is due to the assumption that the presented level of detail is sufficient for pedestrian dynamics applications.

Under realistic conditions, a pedestrian may begin the fulfillment phase at a location later in time, e.g., due to congestions, capacity issues, or other interferences. Vice versa, pedestrian may visit a location earlier in time, e.g., to a lack of alternative locations. Such conditions can be integrated by implementing the interest function model in a pedestrian simulator (see Section 4).

3.3. Single location occupancy regeneration

The interest function approach models the reoccurring motivation of a pedestrian to visit a specific location. By applying the concept in a computer simulation, the model can describe the interest in a certain location for multiple pedestrians. In an idealized system without spatial based interferences, the occupancy of a location is acquired based on the fulfillment parts of the interest functions for a time frame $[t_i, t_j]$. Figure 4 presents an example occupancy. The occupancy Ψ of location a is regenerated by summing up the fulfillment parts

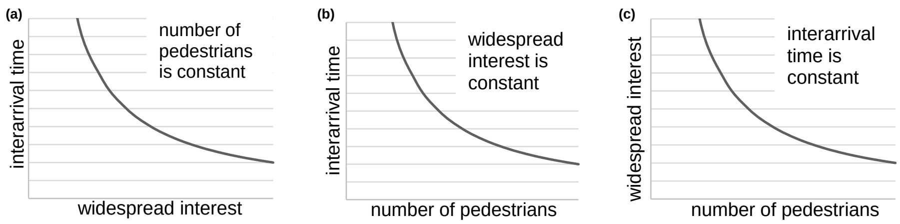

Figure 3:
(a) Qualitative fundamental dependency between the interests in a location for all pedestrians and the mean interarrival time at a location, if the number of pedestrians at a scenario is constant.
(b) Qualitative fundamental dependency between the number of pedestrians at a scenario and the mean interarrival time at a location, if the interest magnitude for a certain location is constant for all pedestrians.
(c) Qualitative fundamental dependency between the number of pedestrians at a scenario and the interest in a location for all pedestrians, if the mean interarrival time at a location is constant.

of ψ_{t,a,t_i,t_j} of all corresponding interest functions of all simulated pedestrians or group P for each discrete simulation time step Δt.

$$\Psi_{t,a,t_i,t_j} = \sum_{1=k}^{P} \lfloor \psi_{k(t,a,t_i,t_j)} \rfloor \tag{8}$$

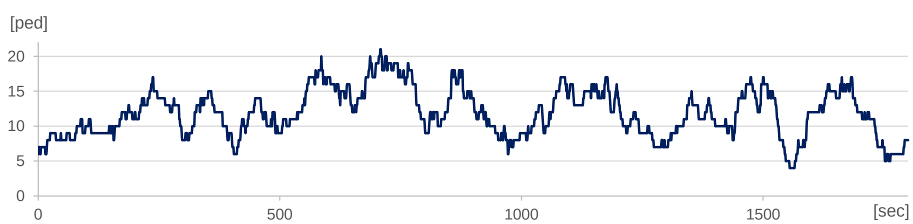

Figure 4:
Occupancy results of an example simulation. The abscissa describes the time in seconds and the ordinate describes the number of pedestrians.

Pedestrians mostly have an initial interest in a certain objective before an initial observation time frame begins at t_0. We account for this property by introducing a virtual relaxation time shift based on a value τ.

$$\tau_{a,t_0,t_1} = \eta_{a,t_0,t_1} \cdot \max(\nu_{a,t_0,t_1}) + \max(\mu_{a,t_0,t_1}) \tag{9}$$

The value τ describes a past point in time were the interest calculation has started. Additionally, the beginning initial interest magnitude is randomized for this starting point in time. If the relaxation and the randomization are ignored, this leads to unrealistic interest functions. Consequently, the occupancy will follow an unrealistic form, which is generated by starting all interest functions at the threshold Ω_{mit} at t_0 and by emerging anomalies based on the interarrival times distribution. The error can be identified by multiple simulation runs because the results of simulations utilized with incorrect τ values yield data which are not in accordance with measured real data (see Section 3.4). Figure 5 shows the mean occupancy results for three times 100 example simulations, each calculated with a different τ value.

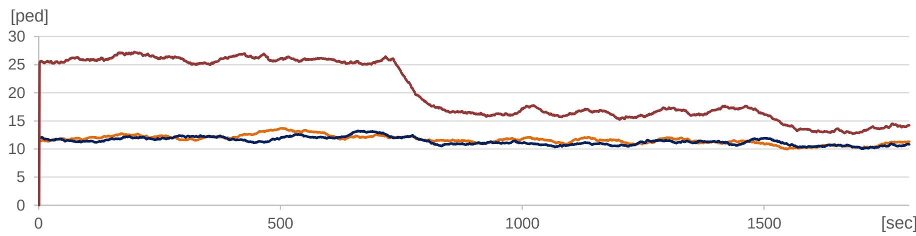

Figure 5:
Mean occupancy over time, each out of 100 example simulations, as a result of three different τ values and randomized initial interest magnitudes. The first function (brown/red) without a time shift. The second function (orange) has a 1/3 time shift, and the third function has a correct time shift (blue). The abscissa describes the time in seconds and the ordinate describes the number of pedestrians.

3.4. Single location interest validation

For the sake of model validation, we collected the data of a one-day music festival with approximately 5000 visitors. Different locations at the music festival were captured by camera and the videos were evaluated in post-processing steps [12]. We focused on a single location for an in-depth validation of the model.

The layout of the surveyed festival is presented in Figure 6 (a). The festival ground is a closed system comprising only one entrance and exit, excluding closed emergency exits. The following validation explanations are based on data collected within a 30 minute time frame. The data set begins two hours and 40 minutes after the festival opening at 12:00 noon. The data comprise the examination results of the video footage of a temporary building location at the festival. Additionally, the data of the maximal pedestrian inflow of the festival over time is known. At t_0, the number of pedestrians at the festival is 707, and the inflow of pedestrian on the scenario till t_1 is 467. Therefore, the maximum number of pedestrians is 1174. Figure 6 (b) features the plot of the increasing number of pedestrians during the 30-minute observation time frame, while Figure 6 (c) shows the camera's view of the temporary building. The location's occupancy is assessed by measuring incoming and exiting pedestrians at the temporary building. The occupancy of the temporary building area over the 30-minute time frame conforms to the black plots in Figure 8.In the 30-minute time frame, the maximum capacity of the temporary building was never exceeded, waiting times were less than one second, and no clogging was observed. Hence, the data represents highly normal and relaxed conditions – making it perfectly suitable for genuine validation purposes.

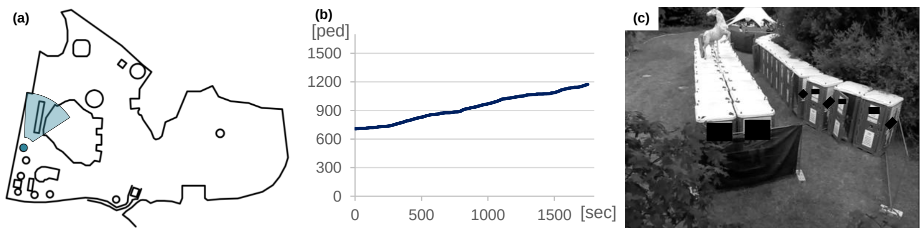

Figure 6:
(a) The festival layout. The camera position is indicated by the blue circle and the camera's view is indicated by the circular segment.
(b) Maximal inflow of pedestrians at the festival in the observed time frame. The abscissa describes the time in seconds and the ordinate describes the number of pedestrians. The time frame starts two hours and 40 minutes after the festival opening.
(c) Temporary building location without visitors and blacked-out company names.

Figure 7 (a) shows the cumulative interarrival time distribution density function, comprising 317 measurements. The cumulative service time distribution function is shown in Figure 7 (b). Additionally, we found out that the mean group size for pedestrians who approach the location together is two.

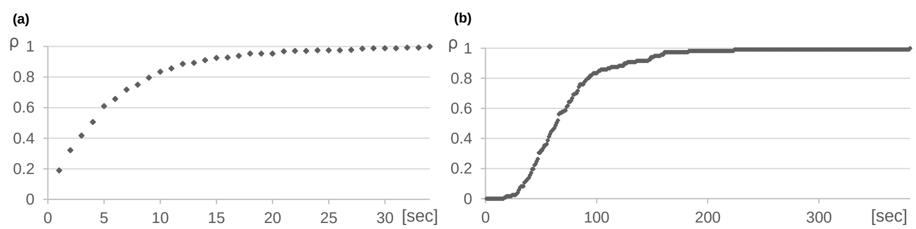

Figure 7:
(a) Cumulative density function of the temporary building's interarrival time distribution. The abscissa describes the interarrival times in seconds and the ordinate describes the cumulative probability ρ.
(b) Cumulative density function of the temporary building's service time distribution. The abscissa describes the service times in seconds and the ordinate describes the cumulative probability ρ

For the sake of model validation, we recreated the occupancy data of the music festival as accurately as possible via computer simulations. The goal was to reproduce the linear fit, the mean, the minimum, the maximum, and the standard deviation of the real occupancy data. The occupancy simulation results are based on probabilities; thus, the regenerated occupancy of a single simulation cannot be directly compared to real data. Hence, we run 500 simulations to account for the comparison problem. The simulations are parameterized with the data of the 30 minute time frame of the music festival and we found that the models' value of α is 1.1502 and β is 0.2703 by stepwise optimization regarding the mean occupancy. In Figure 8, we present the best and the worst results of the 500 simulations of the music festival regarding least squared differences. The statistical mean data of the simulation is compared to the real data in Table 1.

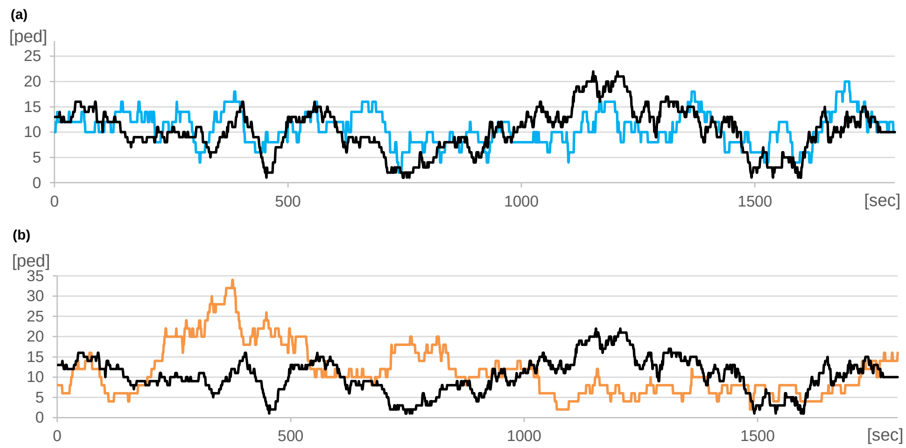

Figure 8:
The black plots represent each the same measured occupancy. The abscissa describes the time in seconds and the ordinate describes the number of pedestrians occupying the location. (a) The blue plot is the best-fitting occupancy simulation result regarding least squared differences. (b) The orange plot is the worst-fitting occupancy simulation result regarding least squared differences.

	Real	Simulation	|Error|	Error%
E [ped]	10.367	10.537	0.17	1.6398
σ [ped]	4.3625	4.375	0.0125	0.2865
maximum [ped]	22.0	23.508	1.508	6.8545
minimum [ped]	1.0	1.268	0.268	26.8

Table 1: Comparison of the simulation results and the real occupancy data of the music festival case study. The simulation results comprise the mean results of 500 interest simulations.

Pedestrian simulations are not to be seen as simulations of deterministic systems, but as an approach to reconstruct the complexity of pedestrian decisions within reasonable bounds. These bounds are hard to acquire and can only be evaluated by running a very large number of simulations. Hence, we run 450k interest simulations for the music festival case study – of which the results are represented in Figure 9. The results describe the distribution of the y-intercepts and the slopes for the linear fittings of the simulations. The position of the real slope and y-intercept is indicated in Figure 9 (b). Simulation results that approximate the real linear fit of the results are quite frequent. At the same time, the simulation provides a wide range of more extreme results which account for unpredictable properties of pedestrian behavior. Nonetheless, such extreme results are less frequent and stay in realistic limits regarding the minimal and maximal number of visitors of the temporary building.

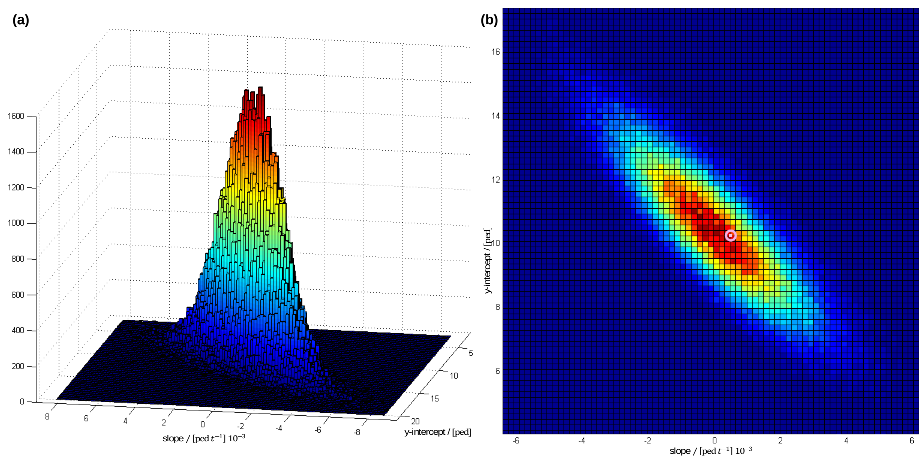

Figure 9:
(a) 3D histogram of the slopes and y-intercepts of 450k simulations of the music festival case study.
(b) Top view of the 3D histogram of the slopes and y-intercepts of 450k simulations of the music festival case study. The pink marker indicates the position of the measured real data slope and y-intercept.

4. The interest function model in multi-location simulations

In this Section, we describe how the model is integrated into existent pedestrian simulators. We implemented our model according to our integration concept and were able to show that the model can improve predictions of pedestrian destination choice in comparison to the widely used origin-destination (OD) matrix approach[2]. The real data for comparing the models is acquired at our case study, a student career fair. Drawing on the fact that there are several identifiable locations present at the fair, we are able to provide practical evidence that the model can be used for more multi-location scenarios.

4.1. Model integration in microscopic simulators

The interest function model can be coupled to microscopic pedestrian models and simulators. In contemporary pedestrian dynamics research, the coupling of models is an established approach [13, 33, 40]. The goal of model coupling

[2]The OD matrix method is a model that is not psychologically grounded. Still, we use it for comparison due to its high prominence and its applicability in microscopic pedestrian simulations. Furthermore, there are no other suitable pedestrians' destination choice models available that are based on psychological findings, are designed to be used in a microscopic pedestrian simulation, and are well known.

is to assemble different approaches, each with specific features and purposes, to create more sophisticated models. The differentiation between strategic, tactical, and operational behavior according to Hoogendoorn and Bovy [30] is in fact a coupling of models (see Section 2).

Figure 10 shows a pedestrian-specific behavioral model architecture. The architecture describes the integration of the interest function model into the strategic, tactical, and operational behavior modeling concept. In a microscopic simulator, each pedestrian is simulated individually; thus, they interact with other simulated pedestrians and the simulated environment. The behavior of each virtual pedestrian is described by the three different models, each respectively implemented on the strategic, tactical, and operational layers. Here, the tactical and operational behavior models are handled as black boxes. Typical examples for tactical models that could be used in this architecture are described by Hartmann [26] or Geraerts and Overmars [24]. As an operational model, the concept of Helbing et al. [27] or Seitz and Köster [51] can be used. The strategic behavioral model in the architecture is coupled with the interest function model. Therefore, the interest function is the source of the interest, drive, will, or motivation for the strategic destination choice method. We have already implemented the proposed architecture in previous work [35]. In Section 4.2, we also provide an implementation based on the work of Shao and Terzopoulos [53].

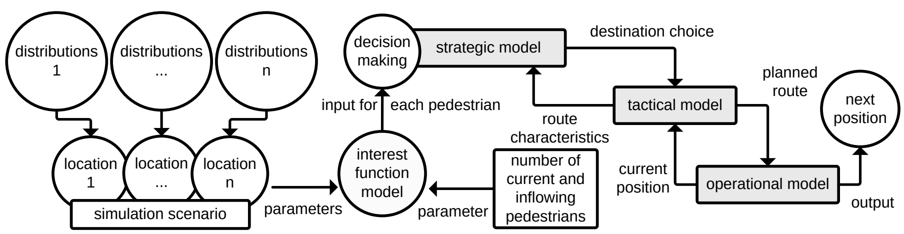

Figure 10:
The strategic, tactical, and operational pedestrian behavioral concept of Hoogendoorn and Bovy [30], extended by the interest function model. The parameters are associated to locations and time frames of the simulation scenario. The results of the interest function model are the interest magnitudes for each pedestrian in each location. The interest magnitudes of the pedestrians are passed on to the strategic behavioral model as a decision basis.

4.2. Computational model comparison

We surveyed a student career fair with cameras and used the collected data to show that the pedestrian interest model is applicable for multiple locations and superior to the origin-destination matrix (OD matrix) approach. Figure 11 (a) presents the camera's visual field of an area at the student career fair. We extracted the geometry layout of the area as a scenario layout for our pedestrian computer simulations. The geometry layout is shown in Figure 11 (b). The scenario comprises five sub-locations (1 to 5) and frequently used doorways (A to E). The simulation input data are the interarrival time distributions, the service time distributions, and the pedestrian inflow at the student career fair. Similarly to the music festival case study, we collected the data in a post-processing step. The time frame associated to the data is approximately 33 minutes and 20 seconds. The exit-interarrival times of the doorways are used in the same fashion as the interarrival times were applied for the locations. Naturally, we define the service time duration of an exit to be zero.

The computer simulations were executed in our generic pedestrian simulator[3] *MomenTUMv2*, whose implementation includes the architecture of Section 4.1. The implemented operational model is a social force model [27], and the tactical model is a shortest path routing concept based on Dijkstra's algorithm [18]. We used the algorithm of Kneidl et al. [39] to generate routing graphs. As strategic models, we implemented the interest function model coupled with the task queuing concept of Shao and Terzopoulos [53] and the OD matrix approach. For each of the strategic models we run pedestrian computer simulations to compare the results. For both simulation cases, we simulated 5000 seconds and clipped the first 3000 seconds of the simulation results. This ensures that the simulations reach a stable state. The entry-interarrival times for doorways were used to calibrate the pedestrian generators. Simulated pedestrians are removed from the system if a doorway goal location is reached. Generally speaking, the simulations for both strategic model approaches are executed in the exact same computational environment and for the same simulation scenario layout.

First, we simulated the scenario with the OD matrix approach. The OD matrix strategic model distributes pedestrians according to the number of visitors measured at the locations. Therefore, the algorithm randomly selects a new destination based on the locations' arrival percentages every time a pedestrian finishes visiting a location. We prohibit pedestrians from visiting the same location in a row by probability adjustments because highly interesting locations would otherwise be heavily overestimated by the OD matrix model. A drawback of the OD matrix approach is that it does not feature a service time concept. We added our fulfillment phase term to the OD matrix model to enable virtual pedestrians to dwell at a location for certain a duration. If the mean, median, minimal, or maximal service time values are used, the pedestrians will either congest locations or visit them to fast to account for useful occupancy data.

We implemented our interest function model by integrating it to the goal queuing concept of the strategic model of [53][4]. Hence, each virtual pedestrian implements an interest function for each location and doorway of the career fair. In the model, destinations are added to a pedestrian's goal stack according the interest magnitude. A pedestrian will always visit the location at the top of the goal stack. If other interest magnitudes reach the linear fulfillment phase and the goal is not on the top of the stack, the algorithm queues the goals

[3]https://www.cms.bgu.tum.de/en/research/projects/31-forschung/projekte/456-momentum

[4]The strategic model of Shao and Terzopoulos [53] offers a direct interface to implement a desire (interest) function – but it does not provide a mathematical desire concept.

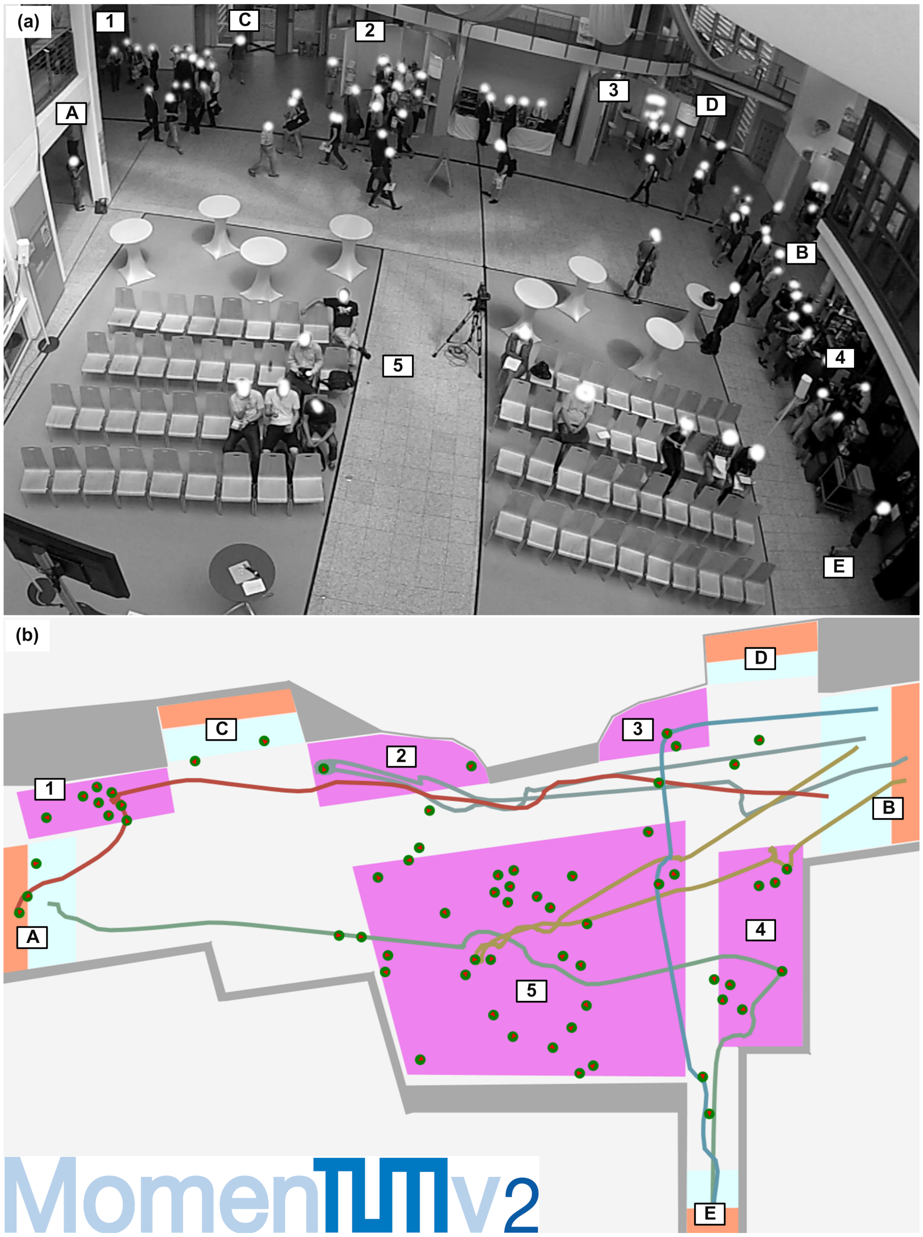

Figure 11:
(a) The fish-eye camera's view of the student career fair scenario.
(b) A screen-shot of the pedestrian computer simulation utilizing the interest function model. The visible paths represent the walking trajectory describing the visiting pattern of some pedestrians. The simulation layout of the scenario was extracted from a building information model [44].

accordingly and freezes the execution of the corresponding interest function. By applying this approach, we can account for preemptive fulfillment behavior as well as for delayed fulfillment, which emerges due to microscopic effects and competing interests. Figure 12 presents a state-chart that describes the destination choice model. The constants α and β of the interest model are taken from the music festival case study of Section 3.4. Figure 11 (b) presents an image of the visualization of the interest-based pedestrian simulation.

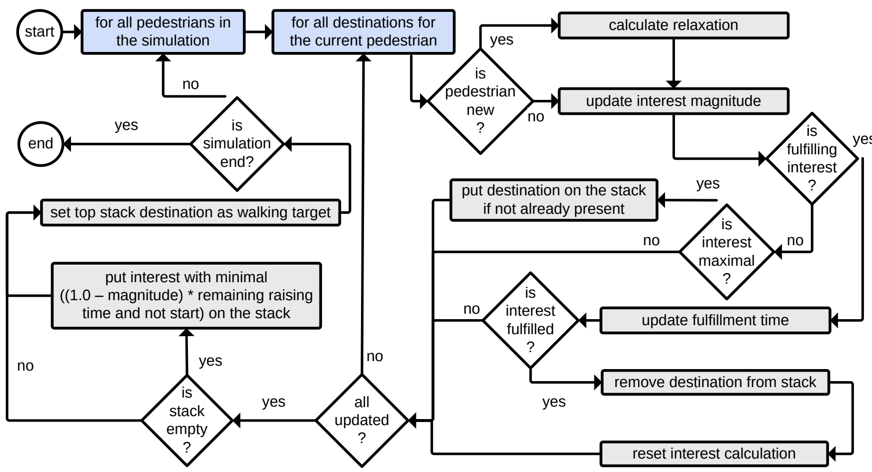

Figure 12:
A state-chart describing how pedestrian select a destination based on the interest function magnitudes including the queuing concept of Shao and Terzopoulos [53]. The decision points regarding the interest magnitude on the right hand side always refer to the current destination of the loop.

In Table 2 and Figure 13, we summarize the comparison data of the OD matrix and interest function simulation results. The results are each the mean results of 150 simulations of the case study scenario; thus, we present the mean of the means and the mean of the standard deviations. To calculate the results, we measured the generated occupancy at each location computationally. For doorways, we measured the number of pedestrians leaving the simulation scenario regarding a time discretization of one second. The real data sets are also discretized on the seconds scale. As the results prove, the relative performance improvement of the interest function model compared with the OD matrix is 150.39% for the means and 6.99% for the standard deviations. In general, the OD matrix model generates a very homogeneous occupancy for each location. Nonetheless, it accounts little for variations of the dynamic destination selection of pedestrians. We realized that the resulting variations in the OD matrix simulations could most probably be improved by introducing the fulfillment phase term. This is especially recognizable for doorways without service times, for which the results of both models are quite similar. Pedestrians visiting a doorway are computationally removed from the simulation scenario, so no continuous visiting concept is necessary for them. Using this argumentation, we can determine that the interest function model improves simulations in which pedestrians do not simply leave a system (e.g. evacuations) but travel within the system. This is especially true for location 1 and 5, which include long service durations.

	real E	real σ	ΔE	ΔE%	$\Delta\sigma$	$\Delta\sigma$%
A	0.337	0.66155	-0.01829	-5.4273	-0.00024	-0.03656
B	0.4	0.71572	-0.00101	-0.2525	0.00931	1.30078
C	0.0265	0.18389	0.00413	15.57233	0.02832	15.40122
D	0.018	0.17802	-0.00091	-5.05556	-0.00393	-2.20773
E	0.0515	0.2447	0.00991	19.24919	0.02235	9.13415
1	9.449	1.6667	7.65795	81.04508	-0.0754	-4.52417
2	3.2445	1.3366	0.18186	5.60518	0.17527	13.11304
3	1.896	1.5111	0.41415	21.84353	-0.33224	-21.98692
4	3.8625	2.4242	-0.40755	-10.55137	-0.24139	-9.95732
5	39.967	5.4084	11.33554	28.36225	0.36548	6.75761
sum			19.17579	150.39083	-0.05248	6.9941

Table 2:
The simulations' occupancy results for the OD matrix and the interest function in comparison to the real data set. The values describe the relative accuracy of the interest function model in comparison with the OD matrix regarding the measured data. The interest function model is superior if a positive value is given and inferior if a negative value is shown. The Δ calculations are based on the formula $|\text{real data} - \text{OD data}| - |\text{real data} - \text{interest data}|$.

5. Discussion

Pedestrians tend to visit certain locations based on some kind of motivation. Even if the motive itself cannot be assessed, evaluating real data helps to model interest as a mathematical function. As shown in Sections 3.4 and 4.2, the introduced approach improves pedestrian destination choice models. Nonetheless, some challenges will have to be addressed in future.

As briefly described in Section 3.2, groups often travel and visit locations together. Each pedestrian in a group should have a set of own interest functions – but these are still homogenized with the interests of other group members. The current approach models groups by a joint interest function shared by the group members. A challenge for the interest function model is to include a group interest function that can be split up or joined together, based on various spatial, temporal, and social dependencies.

The distributions used for the parameterization of the interest calculation are the interarrival times and the service times. Both distributions inherit critical aspects. For example, if a set of pedestrians visits a location more frequently and another set of pedestrians ignores the location completely, then a visit-blurring effect occurs. The discrepancy in visits will lead to interarrival time distributions that are averaged. This challenge can be addressed by using a classification analysis to identify sub-populations. The same argument holds true for service

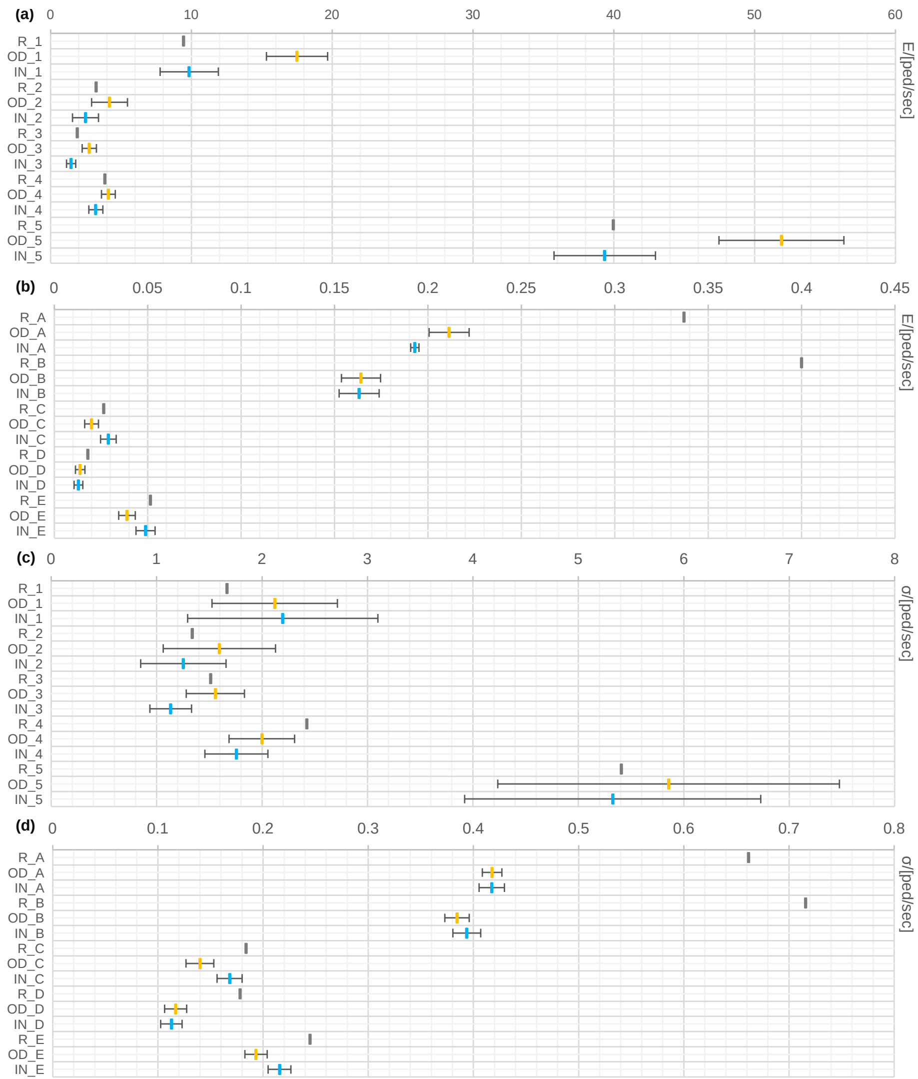

Figure 13:
The mean occupancy results in plot (a) and (b) as well as the standard deviation results in plot (c) and (d), based on 150 OD matrix simulations (OD) and on 150 interest function based simulations (IN) in comparison to the real data (R). The error plots describe the standard deviation of the data regarding the variances within 150 simulations.

times. In general, poorly measured or non-representative distributions lead to imprecise visiting pattern forecasts. Since simulation-based predictions usually required parameters a-priori, it is necessary to identify and rely on classes of events and visitors. This emphasizes that a-priori information of poor quality will lead to a less suitable interest function model.

Finally, interest alone is not the only factor that drives strategic pedestrian behavior. Thus, it is mandatory for further research to include other influence factors in a mathematical fashion and based on psychological findings. Similarly to the interest concept, the new functions will serve as input to strategic behavior models. We assume that a high level spatial cognitive approach for strategic pedestrian behavior modeling must feature multiple input functions as well as an internal pedestrian state system. Initial approaches to holistic cognitive models were already developed by [61] and [35], but these might be in need of further research.

6. Conclusion

In this work we introduced a new methodological framework to model pedestrians' interests or preferences in locations. Interest is a fundamental factor for pedestrian decision making with respect to the next location to visit. The interest function model is especially suitable for simulations in which pedestrians do not simply leave a scenario (e.g. evacuations) but travel within the scenario. In contemporary research, the shortcomings of strategic pedestrian behavior models are often grounded in insufficient soundness regarding mathematical descriptions or psychological background. We addressed this research gap by presenting the interest function concept, which models a tendency source for pedestrian destination choice models.

The interest function model is grounded on the goal-related memory accessibility concept, which is an approach found in psychological research. Additionally, fundamental dependencies of pedestrian behavior were taken into account. By combining these interdisciplinary aspects, we created the mathematics-based interest function model. The model describes the re-occurring and time-dependent internal drive to visit a certain location. We provided evidence that the interest function model is able to represent the occupancy at a specific location of our first case study accurately. The results also show that the model operates in realistic bounds and accounts for the high internal variability of pedestrian destination choices. In addition, we designed the interest function model as an includable component for existing pedestrian destination choice models. Therefore, we provide a pedestrian behavior architecture that guides the coupling of the interest function model to existing behavioral models. For a proof of concept, we implemented the architecture and extended a strategic model found in the literature. Additionally, we compared simulation results of the extended model to simulation results of the widely used origin-destination matrix approach for our second multi-location case study. Our simulation results provided evidence that the interest function model outperforms the origin-destination matrix especially for locations that exhibit long service durations and a high number of visitors.

The interest function model is a validated new framework to model pedestrians' interests to visit a single as well as multiple locations. Still, some challenges are left. An interest function that accounts for groups is far more complex than assumed, so there has to be further research. Additionally, destination choice models are in need of other psychology-based and mathematically modeled decision functions because the literature seldom provide appropriate function that are implementable in microscopic pedestrian simulations. For this reasons, future model approaches will be designed to account for other generic and psychology-based sources for pedestrian destination choice.

Acknowledgments

This work is supported by the Federal Ministry for Education and Research (Bundesministerium für Bildung und Forschung, BMBF), project MultikOSi, under grant FKZ 13N12823.

We would like to thank Daniel H. Biedermann and Michael Seitz for fruitful discussions regarding the paper's topic. Additionally, we thank Oliver Handel, Daniel H. Biedermann, and our student assistants for helping us evaluating the festival data as well as Alex Braun for the sketch of the festival layout.

Appendix

The interest function model is designed as a framework to be used in pedestrian simulators. For the sake of better understanding as well as an easier model integration, we present the algorithm 1 describing the interest function model in pseudo-code regarding single location simulations.

Algorithm 1 Interest function model for single location simulations

function *output* InterestSimulationSingleLocation(*tmax*, *peds*, *gSize*, *inCount*, *arrCount*, *arrDist*, *serDist*)
  Initialization:
  $\alpha \leftarrow 1.1502; \beta \leftarrow 0.2703; max \leftarrow 0.99; min \leftarrow 0.01; h \leftarrow -1.55$
  $k \leftarrow -\alpha/(inCount^h - (inCount \cdot \beta)^h)$
  $w \leftarrow -k/inCount^h; sp \leftarrow \alpha/arrCount^h + w; peds \leftarrow \lceil peds/gSize \rceil$
  $relax \leftarrow inCount \cdot \max(arrDist) + \max(serDist)$
  $inx, inHalf, finLen \leftarrow$ array of size $peds$ with zeros
  $output \leftarrow$ array of size $tmax \times peds$
  Relaxation:
  for $ped \leftarrow 1$ to $peds$ **do**
    $finLen[ped] \leftarrow$ draw from $serDist$
    $curArr \leftarrow sp \cdot inCount \cdot$ draw from $arrDist$
    $sInx =$ random of $[0, 1] \cdot (curArr + finLen[ped])$
    while *true* **do**
      if $relax - sInx < 0$ **then**
        $sInx \leftarrow sInx - (finLen[ped] + curArr)$
        $inx[ped] \leftarrow \text{round}(-curArr/2 + (relax - sInx))$
        $inHalf[ped] \leftarrow \text{round}(curArr/2)$
        break while
      else
        $finLen[ped] \leftarrow$ draw from $serDist$
        $curArr \leftarrow sp \cdot inCount \cdot$ draw from $arrDist$
        $sInx \leftarrow sInx + curArr + finLen[ped]$
      end if
    end while
  end for
  Simulation:
  for $t \leftarrow 1$ to $tmax$ **do**
    for $ped \leftarrow 1$ to p **do**
      if $inx[ped] < inHalf[ped])$ **then**
        $output[t][ped] \leftarrow (1 + e^{-inx[ped]/(inHalf[ped]/-\ln(1/max-1))})^{-1}$
      else if $inx[ped] < inHalf[ped] + finLen[ped]$ **then**
        $output[t][ped] \leftarrow gSize$
      else
        $finLen[ped] \leftarrow$ draw from $serDist$
        $inHalf[ped] \leftarrow \text{round}(0.5 \cdot sp \cdot inCount \cdot \text{draw from } arrDist)$
        $inx[ped] \leftarrow \text{round}(-inHalf[ped]); output[t][ped] \leftarrow min$
      end if
      $inx[ped] \leftarrow inx[ped] + 1;$
    end for
  end for
  return *output*
end function

References

[1] Alonso-Marroquín, F., Busch, J., Chiew, C., Lozano, C., Ramírez-Gómez, Á., 2014. Simulation of counterflow pedestrian dynamics using spheropolygons. Physical Review E 90 (6), 063305.

[2] Anderson, J. R., 1983. A spreading activation theory of memory. Journal of Verbal Learning and Verbal Behavior 22 (3), 261–295.

[3] Anderson, J. R., 1996. ACT: A simple theory of complex cognition. American Psychologist 51 (4), 355–365.

[4] Anderson, J. R., 2010. Cognitive Psychology and Its Implications: Seventh Edition. New York: Worth Publishing.

[5] Anderson, J. R., Milson, R., 1989. Human memory: An adaptive perspective. Psychological Review 96 (4), 703–719.

[6] Anderson, J. R., Schooler, L. J., 1991. Reflections of the environment in memory. Psychological Science 2 (6), 396–408.

[7] Arentze, T. A., Timmermans, H. J. P., 2009. A need-based model of multi-day, multi-person activity generation. Transportation Research Part B: Methodological 43 (2), 251 – 265.

[8] Balke, T., Gilbert, N., 2014. How do agents make decisions? a survey. Journal of Artificial Societies and Social Simulation 17 (4), 13.

[9] Bandini, S., Rubagotti, F., Vizzari, G., Shimura, K., 2011. An agent model of pedestrian and group dynamics: Experiments on group cohesion. In: AI*IA 2011: Artificial Intelligence Around Man and Beyond. Vol. 6934 of Lecture Notes in Computer Science. Springer Berlin Heidelberg, pp. 104–116.

[10] Bauer, D., Gantner, J., 2014. Including route choice models into pedestrian movement simulation models. In: Pedestrian and Evacuation Dynamics 2012. pp. 713–727.

[11] Becker-Asano, C., Wachsmuth, I., 2010. Affective computing with primary and secondary emotions in a virtual human. Autonomous Agents and Multi-Agent Systems 20 (1), 32–49.

[12] Biedermann, D. H., Dietrich, F., Handel, O., Kielar, P. M., Seitz, M., 2015. Using raspberry pi for scientific video observation of pedestrians during a music festival. Tech. rep., Technische Universität München.

[13] Biedermann, D. H., Kielar, P. M., Handel, O., Borrmann, A., 2014. Towards transitum: A generic framework for multiscale coupling of pedestrian simulation models based on transition zones. Transportation Research Procedia 2, 495–500.

[14] Bierlaire, M., Robin, T., 2009. Pedestrians choices. In: Pedestrian Behavior. Models, Data Collection and Applications. pp. 1–26.

[15] Borgers, A. W. J., Timmermans, H. J. P., 1986. A model of pedestrian route choice and demand for retail facilities within inner-city shopping areas. Geographical Analysis 18 (2), 115–128.

[16] Canca, D., Zarzo, A., Algaba, E., Barrena, E., 2013. Macroscopic attraction-based simulation of pedestrian mobility: A dynamic individual route-choice approach. European Journal of Operational Research 231 (2), 428–442.

[17] Danalet, A., Farooq, B., Bierlaire, M., 2014. A bayesian approach to detect pedestrian destination-sequences from wifi signatures. Transportation Research Part C: Emerging Technologies 44, 146 – 170.

[18] Dijkstra, E. W., 1959. A note on two problems in connexion with graphs. Numerische Mathematik 1 (1), 269–271.

[19] Dijkstra, J., Timmermans, H. J. P., Jessurun, J., 2014. Modeling planned and unplanned store visits within a framework for pedestrian movement simulation. Transportation Research Procedia 2, 559–566.

[20] Ferguson, P., Friedrich, E., Karimi, K., 2012. Origin-destination weighting in agent modelling for pedestrian movement forecasting. In: Eighth International Space Syntax Symposium. p. 8153.

[21] Förster, J., Liberman, N., Friedman, R. S., 2007. Seven principles of goal activation: A systematic approach to distinguishing goal priming from priming of non-goal constructs. Personality and Social Psychology Review 11 (3), 211–233.

[22] Förster, J., Liberman, N., Higgins, E. T., 2005. Accessibility from active and fulfilled goals. Journal of Experimental Social Psychology 41 (3), 220–239.

[23] Gärling, T., 1999. Human information processing in sequential spatial choice. Wayfinding behavior: Cognitive mapping and other spatial processes, 81–98.

[24] Geraerts, R., Overmars, M., 2007. The corridor map method: A general framework for real-time high-quality path planning. Computer Animation and Virtual Worlds 18 (2), 107–119.

[25] Haklay, M., O'Sullivan, D., Thurstain-Goodwin, M., Schelhorn, T., 2001. "so go downtown": simulating pedestrian movement in town centres. Environment and Planning B: Planning and Design 28 (3), 343–359.

[26] Hartmann, D., 2010. Adaptive pedestrian dynamics based on geodesics. New Journal of Physics 12 (4), 043032.

[27] Helbing, D., Farkas, I., Vicsek, T., 2000. Simulating dynamical features of escape panic. Nature 407 (6803), 487–490.

[28] Helbing, D., Mukerji, P., 2012. Crowd disasters as systemic failures: analysis of the love parade disaster. EPJ Data Science 1 (1), 1–40.

[29] Hoogendoorn, M., van Lambalgen, R., Treur, J., 2011. An integrated agent model addressing situation awareness and functional state in decision making. In: Agents in Principle, Agents in Practice. Vol. 7047 of Lecture Notes in Computer Science. pp. 385–397.

[30] Hoogendoorn, S. P., Bovy, P. H. L., 2004. Pedestrian route-choice and activity scheduling theory and models. Transportation Research Part B: Methodological 38 (2), 169–190.

[31] Hoogendoorn, S. P., Bovy, P. H. L., Daamen, W., 2001. Microscopic pedestrian wayfinding and dynamics modelling. In: 1th International Conference on Pedestrian and Evacuation Dynamics. pp. 124–154.

[32] Hu, N., Lees, M. H., Zhou, S., 2013. A pattern-based modeling framework for simulating human-like pedestrian steering behaviors. In: 19th ACM Symposium on Virtual Reality Software and Technology. pp. 179–188.

[33] Ijaz, K., Sohail, S., Hashish, S., 2015. A survey of latest approaches for crowd simulation and modeling using hybrid techniques. In: 17th UKSIM-AMSS International Conference on Modelling and Simulation. pp. 111–116.

[34] Khan, S. D., Vizzari, G., Bandini, S., 2014. Identifying sources and sinks and detecting dominant motion patterns in crowds. Transportation Research Procedia 2, 195–200.

[35] Kielar, P. M., Handel, O., Biedermann, D. H., Borrmann, A., 2014. Concurrent hierarchical finite state machines for modeling pedestrian behavioral tendencies. Transportation Research Procedia 2, 584–593.

[36] Klüpfel, H., 2007. The simulation of crowd dynamics at very large events - calibration, empirical data, and validation. In: 3th International Conference on Pedestrian and Evacuation Dynamics. Springer, pp. 285–296.

[37] Kneidl, A., 2013. Methoden zur abbildung menschlichen navigationsverhaltens bei der modellierung von fußgängerströmen. Ph.D. thesis, Technische Universität München.

[38] Kneidl, A., Borrmann, A., 2011. How do pedestrians find their way? results of an experimental study with students compared to simulation results. In: Proceedings of Emergency Evacuation of People from Buildings. Warsaw, Poland, pp. 163–172.

[39] Kneidl, A., Borrmann, A., Hartmann, D., 2012. Generation and use of sparse navigation graphs for microscopic pedestrian simulation models. Advanced Engineering Informatics 26 (4), 669–680.

[40] Kneidl, A., Hartmann, D., Borrmann, A., 2013. A hybrid multi-scale approach for simulation of pedestrian dynamics. Transportation Research Part C: Emerging Technologies 37, 223–237.

[41] Kwak, J., Jo, H.-H., Luttinen, T., Kosonen, I., 2014. Modeling pedestrian switching behavior for attractions. Transportation Research Procedia 2, 612–617.

[42] Liddle, J., Seyfried, A., Klingsch, W., Rupprecht, T., Schadschneider, A., Winkens, A., 2009. An experimental study of pedestrian congestions: influence of bottleneck width and length. arXiv preprint arXiv:0911.4350.

[43] Masicampo, E., Ambady, N., 2014. Predicting fluctuations in widespread interest: Memory decay and goal-related memory accessibility in internet search trends. Journal of Experimental Psychology: General 143 (1), 205–214.

[44] Mayer, H., Klein, W., Frey, C., Daum, S., Kielar, P., Borrmann, A., 2014. Pedestrian simulation based on bim data. In: ASHRAE/IBPSA-USA Building Simulation Conference. pp. 425–432.

[45] Moussaïd, M., Helbing, D., Theraulaz, G., 2011. How simple rules determine pedestrian behavior and crowd disasters. Proceedings of the National Academy of Sciences 108 (17), 6884–6888.

[46] Newmark, G. L., Plaut, P. O., 2005. Shopping trip-chaining behavior at malls in a transitional economy. Transportation Research Record: Journal of the Transportation Research Board 1939, 174–183.

[47] Park, J. H., Rojas, F. A., Yang, H. S., 2013. A collision avoidance behavior model for crowd simulation based on psychological findings. Computer Animation and Virtual Worlds 24 (3–4), 173–183.

[48] Pelechano, N., O'Brien, K., Silverman, B. G., Badler, N., 2005. Crowd simulation incorporating agent psychological models, roles and communication. Center for Human Modeling and Simulation University of Pennsylvania.

[49] Peters, C., Ennis, C., 2009. Modeling groups of plausible virtual pedestrians. IEEE Computer Graphics and Applications 29 (4), 54–63.

[50] Seer, S., Bauer, D., Brändle, N., Ray, M., 2008. Estimating pedestrian movement characteristics for crowd control at public transport facilities. In: 11th International IEEE Conference on Intelligent Transportation Systems. IEEE, pp. 742–747.

[51] Seitz, M. J., Köster, G., 2012. Natural discretization of pedestrian movement in continuous space. Physical Review E 86 (4), 046108.

[52] Seyfried, A., Steffen, B., Klingsch, W., Boltes, M., 2005. The fundamental diagram of pedestrian movement revisited. Journal of Statistical Mechanics: Theory and Experiment 2005 (10), P10002.

[53] Shao, W., Terzopoulos, D., 2007. Autonomous pedestrians. Graphical Models 69 (5–6), 246–274.

[54] Silverman, B. G., Johns, M., Cornwell, J., O'Brien, K., 2006. Human behavior models for agents in simulators and games: part i: enabling science with pmfserv. Presence: Teleoperators and Virtual Environments 15 (2), 139–162.

[55] Timmermans, H. J. P., van der Hagen, X., Borgers, A. W. J., 1992. Transportation systems, retail environments and pedestrian trip chaining behaviour: Modelling issues and applications. Transportation Research Part B: Methodological 26 (1), 45–59.

[56] Truong, H., Beck, E., Julie, D., Adam, C., 2013. Developing a model of evacuation after an earthquake in lebanon. arXiv preprint arXiv:1312.5941.

[57] Urbani, L., 2012. Commuters rail sations and pedestrians flows: The hardbrücke station in zurich, switzerland. Procedia-Social and Behavioral Sciences 53, 146–154.

[58] van Wageningen-Kessels, F. L. M., Hoogendoorn, S. P., Daamen, W., 2014. Extension of edie's definitions for pedestrian dynamics. Transportation Research Procedia 2, 507–512.

[59] von Sivers, I., Templeton, A., Köster, G., Drury, J., Philippides, A., 2014. Humans do not always act selfishly: Social identity and helping in emergency evacuation simulation. Transportation Research Procedia 2, 585–593.

[60] Wagner, N., Agrawal, V., 2014. An agent-based simulation system for concert venue crowd evacuation modeling in the presence of a fire disaster. Expert Systems with Applications 41 (6), 2807–2815.

[61] Wijermans, N., Jorna, R., Jager, W., van Vliet, T., Adang, O., 2013. Cross: Modelling crowd behaviour with social-cognitive agents. Journal of Artificial Societies and Social Simulation 16 (4), 1.