Coupling Spatial Task Solving Models to Simulate Complex Pedestrian Behavior Patterns

Peter M. Kieler\textsuperscript{1,2}, André Borrmann\textsuperscript{2}

\textsuperscript{1,2}Chair of Computational Modeling and Simulation, Technische Universität München, Arcistr. 21, D-80333 Munich, Germany
peter.kieler@tum.de; andre.borrmann@tum.de

Abstract: The behavior of pedestrians in urban environments involves different spatial tasks. Typical tasks found in everyday life are: navigating to a destination, searching for an unknown location, queuing (e.g., at a counter), or finding one’s position in a crowd (e.g., in front a stage). In computational pedestrian behavior simulations, models that solve spatial tasks must be linked to and activated at the right conditions to provide versatile pedestrian behavior patterns. In this paper, we propose an integrative and extensible approach to combine such spatial task solving models. Our concept’s core function is to switch control between integrated models based on destination choice commands and perceptual information. Furthermore, we discuss example simulations to which we successfully applied our model. In doing so, we provide evidence that our approach allows to simulate more sophisticated behavior scenarios by coupling different spatial task solving models.

Keywords: pedestrian dynamics, behavior simulation, behavior modeling, model coupling, simulator architecture

1 Introduction

Pedestrian simulations help to study different aspects of pedestrian behavior. Often, simulations only address wayfinding and walking behavior [1]. However, pedestrian behavior involves a lot of different aspects if people interact in non-trivial environments. In a main train station, for example, pedestrians will queue up at a counter to buy tickets, navigate inside the building, and finally wait for their train at the platform. Hence, pedestrians generate high-level behavior patterns by solving multiple spatial tasks. In pedestrian dynamics, behavior is often modeled by an integrated approach of modeling strategic, tactical, and operational behavior [2, 3]. Strategic behavior describes the choosing of a destination to visit, while tactical behavior models refer to finding a navigation path to a certain destination, and operational models describe the walking behavior along a path.

In this paper, our definition of tactical models represents a more generalized view than what typically can be found in literature, as we do not relate tactical models exclusively to routing. Instead, we introduce the idea of spatial task solving models that, depending on the situation, stand for a tactical model that describes queuing, routing, or further spatial behavior. Thus, in pedestrian behavior simulations, spatial tasks are solved by specialized tactical models, which, when coupled, contribute to improve pedestrian simulations by providing a solution to simulate complex pedestrian behavior patterns. To the best of our knowledge, there is no generic and integrative framework that allows to couple different tactical models that were not designed as a single model. This missing coupling framework limits the scope of behavioral patterns in pedestrian simulations, e.g., one cannot combine arbitrary routing and queuing models.

To fill this research gap, we present a spatial task model that combines tactical models in a single framework. The model provides a concept for model switching and integrates smoothly in the existing concepts of behavior model structuring. Therefore, it can be implemented in most microscopic pedestrian simulators. Furthermore, our model is extensible, because further tactical models can be integrated easily.

In the remainder of this paper, we will present the related work, details regarding our model, as well as two simulation studies, providing evidence that our approach works in practice.

2 Related work

Our approach is a method that combines multiple independent tactical models. The coupling of models is a well-established concept in pedestrian dynamics. Model coupling can provide more sophisticated simulation
results or compensate for the downsides of the individual models [4]. For example, the TransiTUM framework couples continuous walking models and cellular automata models in a bidirectional manner to improve computational performance [5]. Our model combination approach is in line with the goals of model coupling, as we improve the simulations by combining independent models as part of the spatial task model. To our best knowledge, the coupling of tactical models has not been addressed before.

Our proposed framework has to interface strategic behavior models to receive high-level behavior commands and to interact with operational models to activate and direct the walking behavior. This interface concept that uses strategic commands to activate routing, as well as walking behavior, is quite common in pedestrian behavior frameworks and simulators [6, 7, 8]. However, these approaches overlook to address the generalizability of the command approach in the context of tactical behavior models.

3 Spatial task model

The spatial task model we propose is a methodology for integrating multiple tactical models that solve different spatial tasks. In doing so, the tactical models are not merely dedicated to navigation- as often defined in literature [2, 3]. The tactical models we address are to be seen as generalized concepts focusing on how pedestrians find a position within the visible space to walk to. This definition embraces routing as well as queuing and many other spatial behavior models. In the subsequent sections, we provide a detailed description of the overall framework, the interfaces between the strategic, tactical, and operational models, as well as the model switching concept.

3.1 Model structure

The structure of the spatial task model is a concept that defines a set of models, some of which are mandatory and some optional. In Fig. 1, we depict the assembly structure of the models, including the information flows between the models. The structure describes a hierarchical approach that places the strategic model, the spatial task model, and the operational model on the highest level. As part of the spatial task model, multiple tactical models are integrated. Possible examples for such tactical models could be routing models, queuing models, or searching models. In general, a routing model is the only mandatory model for applying the spatial task model. However, a routing model will not provide any benefit regarding behavioral patterns if applied on its own.

![Fig. 1 The overall model structure embedded in the concept of strategic, tactical, and operational models.]

3.2 Model interfaces

For interfacing the different models in the structure, we propose to exchange data in form of the pedestrian context, similar as done by [7]. This approach implies that the pedestrian objects are passed on to the model implementations for processing. Hence, each model operates on the state of an individual pedestrian object. This approach requires a microscopic simulation, because each simulated pedestrian is manipulated individually by the model implementation. In general, the strategic model changes the context first followed by the spatial task model operations on the context. Finally, the operational model manipulates the context. This is done for each simulation cycle defined by a time-step length. Fig. 2 provides a visual explanation of the pedestrian data context, the model interfaces, and the data elements.

A pedestrian context has to be present for each pedestrian object within a simulation. Each model may access the data set to perform computations, thereby, updating specific elements of the context.

Strategic models mainly provide the next destination area a pedestrian is supposed to visit. This information is mandatory to conduct consistent model switching later on. Strategic models necessarily require the information whether a pedestrian remains inside or is close to the destination area, e.g., for activating a timer that models the service duration. This proximity information is determined by the spatial task model and stored in the pedestrian context referencing to the current destination. Additionally, some models, e.g., searching models, have to access the information whether a pedestrian is familiar with the surroundings and is aware of the position of the goal area. Therefore, a destination knowledge property set is present in the pedestrian context. The task of updating the aspects of familiarity/knowledge should be addressed in strategic models or in memory concepts.
Operational models determine the current position of a pedestrian. However, these models often also change the velocity, the heading direction, and other walking properties. Nonetheless, the position alone is sufficient for our framework to function properly. Additionally to changing the pedestrian’s position within the context, operational models read the desired position and heading that represents a walking target in the spatial plane the pedestrian is situated in. It is mandatory that the desired position is never occluded by obstacles. If this rule is violated, the pedestrian may get stuck in the environment during simulations.

The spatial task model provides four information items: the current active tactical model, the desired heading direction, the desired walking position, and whether a pedestrian is close to the current destination. In general, the currently active model is determined based on the model switching described below. The desired heading direction and desired position provide visible information to the underlying operation model and are computed by the currently active tactical model. In some queuing models, for example, the desired position is close to the end of the queue and the heading direction points to the next pedestrian in the queue or to the counter. Thus, the desired position and heading direction needs to be updated by the queuing model if a pedestrian moves up. In routing models, the desired heading direction may be obsolete; still, the desired position describes the next navigation node a pedestrian moves to.

It is important to state that the given properties represent the minimal property set for our approach to function. Further properties (e.g., velocity) can always be added. These properties do not interfere with our model and may be mandatory for the implementation of other models. Furthermore, the spatial task model computes additional information that are used for model switching. However, these information are applied only temporarily; thus, there is no need to provide them in the pedestrian data context.

3.3 Model switching

The switching between the tactical models is conducted based on the next destination, perceptual information, and the current position of the pedestrian. These information are always present in the pedestrian context or can be calculated temporarily based on the context. In Fig. 3, we provide a state chart describing the switching procedure. The depicted workflow is executed for each pedestrian after the strategic model computation has finished and before the active tactical model operates. Each operation provided in the decision nodes (rhombus) helps to find the sequence based on the pedestrian context.

Is a destination given? The given destination of a strategic model can be read directly from the pedestrian context. Hence, if the strategic model did not define a destination up to this point or if the previous destination was removed there is no destination data in the context. If no destination is given, the concept activates the ‘do nothing’ behavior. This is basically a dummy model that sets the current position and heading of a pedestrian as the desired position and the desired heading direction for the underlying operational model; thus, the dummy model simulate an idle state. This dummy model could be improved in the future, e.g., by simulating exploration or leisure behavior.

Is the destination visible? To detect if a destination is visible, further algorithms for visibility checks have to be included in the simulation framework in which the integrative spatial task model is implemented. If the perceptual information cannot be provided, the power of the spatial task model is diminished. In the worst case, pedestrians might simply get stuck in the environment. For more details on algorithmic perception implementation for pedestrian simulations, see [8].

Is the destination position known? If the destination is not visible, the implementation determines whether the destination position is known. This can be done by evaluating the destination knowledge set of the pedestrian context. Based on the knowledge information, searching or routing models can be activated. Search models will help to increase the knowledge by navigating the pedestrian in the accessible space until sufficient destination-related information has been acquired, e.g., by reading signs or by exploration [9].

In close proximity to the destination? During routing, the spatial task model checks if the destination is in close proximity to the pedestrian. Here, the proximity is calculated based on a static or dynamic point of interest, e.g., the queue itself or the closest point of a goal area.
This Euclidean distance check is used to activate small-scale tactical interaction with a goal [6]. The qualitative assessment of proximity is highly dependent on the spatial task and the environment the pedestrian is situated in. The correct proximity can be calibrated by field studies. However, we use a value between 0.5m and 2.0m in most cases.

If the pedestrian is close to a destination, the spatial tactical task model chooses the most suited tactical model to solve a task. Which model is applicable can by encoded, e.g., associated with the destination. Thus, each destination may provide a tag that describes what kind of behavior is required at the location. For example, the type could be queuing (at a counter) or exchange (at a subway door). Hence, destination areas provide information concerning the dynamic or static point of interest and the destination type. Both information serve as basis for the spatial task model to choose the correct small-scale tactical model.

4 Example application

To show that our model switching approach is applicable, we present example simulations that build upon the developed spatial task model. First, we present three different tactical models: one for routing, one for queuing, and one for participating in a crowd. These three models are implemented and integrated in our pedestrian simulator MomenTUMv2 [10]. Then, we add the social force model [11] and the cellular stock model [12] for walking behavior. Furthermore, we make use of two different strategic models that provide destination choices, an origin-destination matrix and a cognitive pedestrian model [13, 14]. By using two different strategic and operational models, we show that our interface definitions are sufficient.

4.1 Tactical models

Here, we describe the queuing model of [15], including extensions, and our participating model that describes how pedestrians find their positions in front of an attractor. The wayfinding model is based on Dijkstra’s Algorithm [16]. These three models will be coupled by means of our spatial task model. We do not add a search model, however, approaches for searching behavior have already been investigated [17].

The queuing model of [15] is based on the idea that pedestrian tend to arrange in queues based on arcs. The destination’s point of interest is either the end of the queue or, if there is no queue, the counter. Thus, each pedestrian finds a position to queue up evaluating the next pedestrian in the queue and will choose a position within an arc of $\phi$ with some distance $k$ regarding the heading vector of the next pedestrian. We extended the model by adding a fallback method for the case that a pedestrian is unable to find a valid position within the original arc, to ensure that the pedestrian will not collide with walls and other pedestrians, based on a safety distance of $s$. This is done by rotating the arc stepwise. Fig. 4 provides a visual explanation of the model. The queuing model may also be used for pedestrian groups, which includes further rules [15].

We add a model, which can be coupled with the work of [18], that describes how pedestrians find a position in a location, facing towards a certain point or line of interest. A point of interest is a single point in space that is the center of attention, e.g., an exhibit in a museum. A line of interest is a segment of the border of an area, e.g., the border of a stage. In both cases, our model will find a position facing the interest element. Here, pedestrians might stay close, stay far away, or distribute themselves randomly within the space, including a safety distance $s$ to walls and other pedestrians. In
each case, a computational gamble is the basis for finding the position. For the random assignment, the model will find a random position within the goal location. To model behavior for staying close or staying far away, we reduce the probability of finding a random position that opposes the behavior based on power functions. Hence, we repeat the computational gamble if the found position does not comply with some rules until the upper limit of gambles is reached. The rule for repeating the stay far gamble is \( d_{p,a} / \min_{e} d_{e,a} < r^{1/3} \), with \( d_{p,a} \) as the distance between the pedestrian and the element of interest, \( d_{e,a} \) as the minimal distance from a corner of the area to the element of interest, and \( r \) as a random variable in \([0,0.1]\) ∈ \( \mathbb{R} \). Similarly, the rule for repeating the stay close gamble is \( d_{p,a} / \max_{e} d_{e,a} > r^2 \). If the limit of gambles is reached, the algorithm applies the random rule. Fig. 5 visualizes some of the different participating situations the model can provide. Also, the model can be extended by additional rules for grouping behavior by providing a shared subspace in the goal area.

![Fig. 4 Visual explanation of the arc-based queueing model by [15].](image)

![Fig. 5 Simulation snapshots of pedestrians arrange themselves far away (a) and close by (b) the point of interest at the location, and pedestrians arrange themselves far away (c) and close by (d) the segment of interest at the location.](image)

4.2 Simulation setup

The simulations are conducted in our pedestrian simulation framework MomenTUMv2 [10]. The framework implements the spatial task model. Furthermore, our framework provides a plugin for a commercial CAD system, which helps us to create simulation layouts and which exports the simulation scenario in a XML format. In the XML scenario format, we can define entry, exit and intermediate areas, where the entries are the pedestrian sources, the exits are the sinks, and the intermediate areas are spaces at which pedestrian apply specific forms of spatial behavior, e.g., queuing or participating. For the intermediate areas, a line can be defined that introduce a queue counter or a line of interest respectively.

During the start-up of our simulation, the framework bootstraps all components and executes a pre-processing procedure. For example, the pre-processing comprises the routing graph generation and setting up the scenario objects. Then, the system runs the agent-based simulation by executing the models sequentially. In doing so, the pedestrian objects are passed on to the model implementation (see Sec. 3.2). The simulation runs a fixed number of cycles based on a defined time-step duration until the simulation end-time is reached. In general, each model implementation operates on the pedestrian data context in each simulation cycle; however, the models are able to reject cycles or introduce even smaller time-steps.

4.3 Example simulations

We choose two different simulation scenarios to provide evidence that our approach works in practice. First, we use a large room scenario, which could, for example, represents part of an exhibition. The pedestrians can enter and leave the location in a one-way fashion. Within the room, pedestrians can interact with dif-
different intermediate areas. Here, we apply the cellular stock model \([12]\) for walking, and an origin-destination matrix model for strategic decision making \([14]\). The tactical models are those we presented in Sec. 4.1. The second simulation describes the scenario of a career fair we surveyed with cameras for scientific purposes. For this simulation, we used the social force model \([11]\) for walking and the same tactical models as in the first simulation. We applied a strategic model that builds upon previous research in which the aspects of cognitive modeling are applied to destination choice behavior \([13, 14]\).

In both simulation examples, as shown in Fig. 6, pedestrians switch between navigation, queuing, and participating behavior, based on the destination choice commands. One can observe complex behavior patterns; arranging, queuing, and routing, which arise due to the switching of the different tactical models within the spatial task model. If the only applied model were that of wayfinding behavior, which is the common concept of tactical models, the simulation would result in patterns that cannot be observed in real life. This is can be seen by comparing the images in Fig. 7, which show a video snapshot of the career fair and a simulation snapshot that is based on the wayfinding model only. Here, pedestrians cannot adapt their behavior dynamically so they create unnatural patterns that cannot be found in the video. Furthermore, by combining different operational, tactical, and strategic models in the simulations, we provide evidence that the spatial task model can be used in combination with any pedestrian behavior model that follows our interface definition.

![Fig. 6 Simulation snapshots of an example exhibition (a). The exhibition scenario shows the lattice used cellular automata model applies. The blue area is the entrance, and the orange area is the exit. The career fair scenario is shown in (b). Here, the orange areas are bidirectional doorways. For both snapshots, the light purple spaces are intermediate areas. Furthermore, groups are introduced in (b); thus, the crowds are more compacted than in (a).](image)

![Fig. 7 An image of the video footage of the scenario of the second simulation (a) and a career fair simulation without applying the spatial task model (b). By comparing (b) to Fig 6. (b), it is shown that wayfinding behavior alone cannot provide a solutions to solve complex behavior patterns, because it is mandatory to couple spatial behavior models to correctly interact with the intermediate locations.](image)

5 Conclusion

Typically, pedestrian behavior is defined by three interconnected models: strategic models for destination choice, tactical models for wayfinding, and operational models for walking behavior. However, tactical models can be described in a generalized way. Thus, we defined tactical models as concepts that solve spatial tasks like queuing, wayfinding, or searching. Solving multiple spatial task in a row is typical for pedestrians in more complex environments, e. g., entering a shop, navigating through the shop and choosing goods, queuing at the reg-
ister to pay, and leaving the shop through the front door.

So far, there has been no generic approach to integrate multiple task solving models. In this paper, we presented a spatial task model that enables multiple tactical models to be coupled in a single simulator. The model integrates smoothly into the strategic, tactical, and operational layer concept of pedestrian behavior modeling. Without our approach, simulations scenarios that demands complex spatial behavioral patterns provided by combing specialized tactical models can hardly be simulated with realistic crowd patterns.

Furthermore, we described three tactical models that we coupled in our framework to prove the applicability of our concept. Based on two simulation studies, we showed that our methodology works in practice and can create versatile pedestrian behavior patterns highly independent of the applied strategic and operational models.

In future publications, we will present more details regarding our pedestrian simulation architecture and implemented coupling concepts, which provide advanced options for model combination.

Acknowledgements

This work was 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 all members of the MultikOSi project, especially Daniel H. Biedermann, for helpful discussions. We as also would like to thank our student assistants for contributing to our pedestrian simulator implementation.

References


