Towards multi-layer pedestrian behaviour maps for simulation, tracking, interpretation and indoor navigation

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Abstract: This paper describes the concept of multi-layer pedestrian behaviour maps, their creation through the application of different computational technologies, as well as their usage for different application purposes.

1 Introduction

A pedestrian behaviour map (PBM) describes the movements of individuals through a given spatial scenario including interior (buildings, airports etc.) and exterior spaces (event venues, courts, city parts). These movements are characterized by the behaviour between an individual and his environment – the building, obstacles and other persons. Pedestrian behaviour maps form a suitable basis for improving pedestrian simulation (Kneidl & Borrmann 2011), tracking and interpretation (Burkert et al. 2010) as well as indoor navigation (Schäfer, Straub, Chakraborty 2010).

To realize the aforementioned applications, today static maps are used which represent the location and shape of static topographic entities but do neither describe the pedestrian behaviour nor take into account its dynamic evolution. A typical example is the use of static building floor plans for simulating pedestrian dynamics. Usually, these floor plans do not contain information on temporary constructions or obstacles, such as furniture or flexible walls. As a result, the simulation results may be erroneous or misleading.

To overcome the limitations of static topographic maps, we introduce the concept of multi-layer pedestrian behaviour maps. They are created by continuously enhancing (enriching) an initially static map by behavioural data gained through the evaluation of different sensor data.

2 Automatic Floor Plan Extraction

Initial pedestrian behaviour maps are generated on the basis of static floor plans. These floor plans are directly derived from CAD files via an automatic extraction unit. To provide a general map extraction tool, CAD files in the DXF format are analyzed and parsed for characteristic structures. The data encoded in DXF files consist of several unconnected lines, arcs and poly-lines spread across several drawing layers. Lines depicting doors are typically grouped in one or two layers. The outlines of rooms are often grouped together with labels, pillars and other line information and spread over several layers. To extract this information we use several heuristics that automatically extract the entire structure of a floor (Schäfer, Knapp, Chakraborty 2011). The resulting map already represents a topological model. Rooms are linked with the according doors which serve as interconnection portals. This static map serves as basis for creating the initial behavioural map.

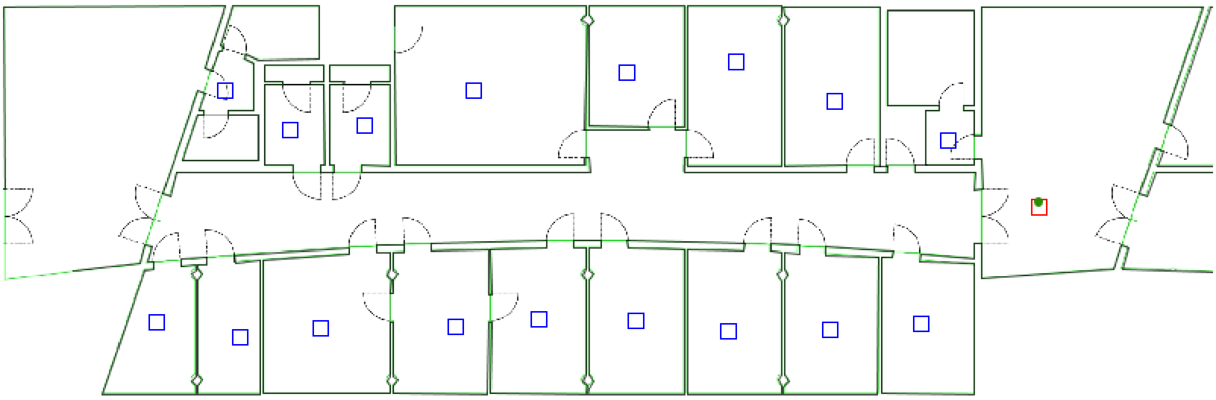

Figure 1: A floor plan forms the basic input for the pedestrian simulation

3 Initial behavioural pedestrian behaviour maps

The initial PBM is generated using a pedestrian dynamics simulator. The simulation and thus the generated map is based on pre-defined topographic maps (floor plans, see Section 2); i.e., it does not include any furniture, modifications in the building structure, or any other topographic information which has an impact on pedestrian navigation behaviour. To simulate pedestrian crowds, a microscopic approach is used, which consists of several layers: A space discretisation layer, a locomotion layer and a navigation layer (Figure 2).

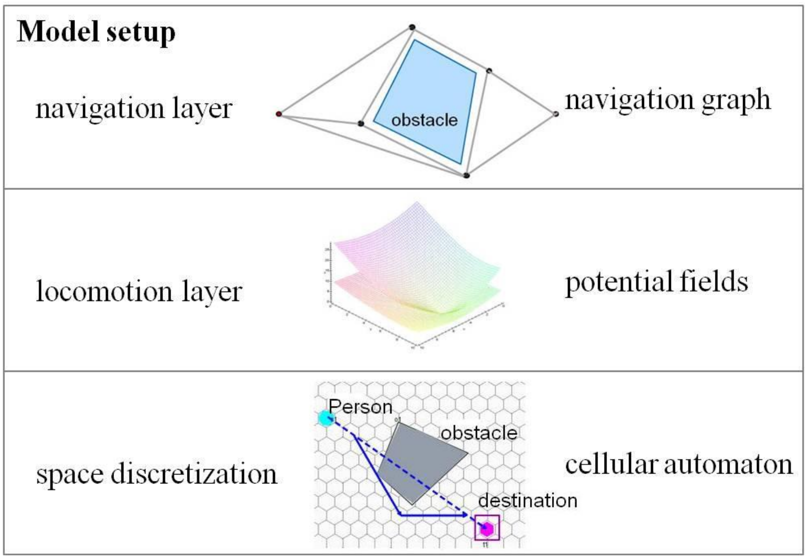

Figure 2: Three layers used in the simulation

The time and space discretisation is modelled by a cellular automaton, which forms the basic layer. To model pedestrians' locomotion, a combination of potentials is applied. Each pedestrian is influenced by different forces: a driving force to the destination, repellent forces of obstacles situated on the way to a destination as well as repellent forces of other pedestrian, who walk within the scenario. These forces are superimposed into one potential field. A value from the potential field is mapped to each cell corresponding to its position. A detailed description of the potentials approach can be found in (Hartmann, 2010).

The third layer describes the navigation layer, which models the spatial orientation of pedestrians. The layer is implemented as a navigation graph, on which different routing strategies can be applied, e.g. pedestrians who are familiar / are not familiar with a location (Höcker et al. 2010, Kneidl & Borrmann 2010, Kneidl et al. 2010).

The simulation is run using all three layers. Simulation results are visualized by sequences of pictures depicting the pedestrians` individual positions in each time step. Flow visualization depicts location, movement direction and velocity of a pedestrian whereas mainstream visualization shows the occupancy rate of individual cells over the entire simulation time (Figure 3).

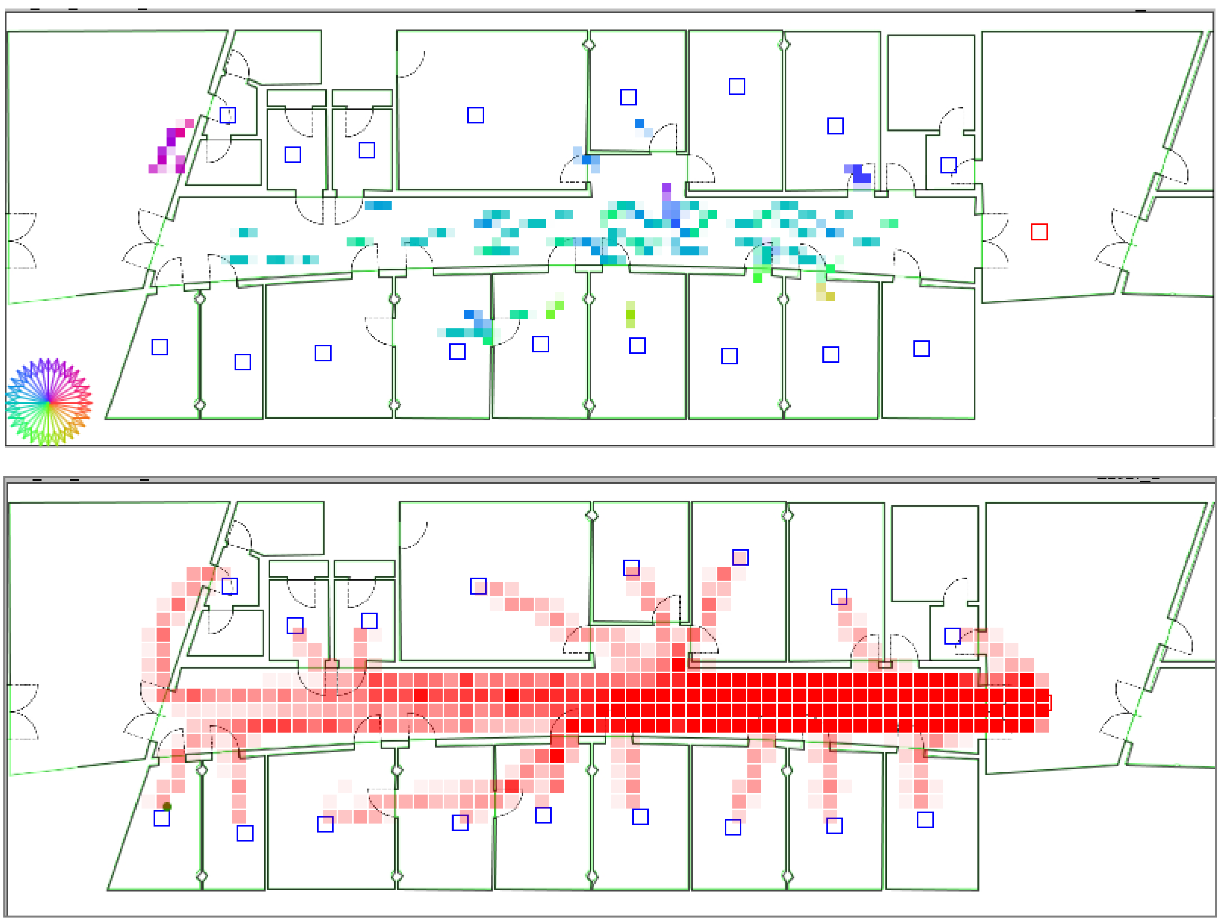

Figure 3: Flow and mainstream visualization used to evaluate the simulation

The evaluation of the simulation result enables the construction of an initial pedestrian behavioural map, which reflects the predicted pedestrian behaviour in the investigated environment. However, as the simulation input is based on purely static information (the floor plan) the simulation is not able to take into account dynamic aspects such as temporary obstacles like chairs or tables, for example. For this reason, the simulation input information is extended by incorporating movement data obtained from two complementary tracking approaches, the first one based on image sequence analysis and the second one based on inertial measurement-based tracking.

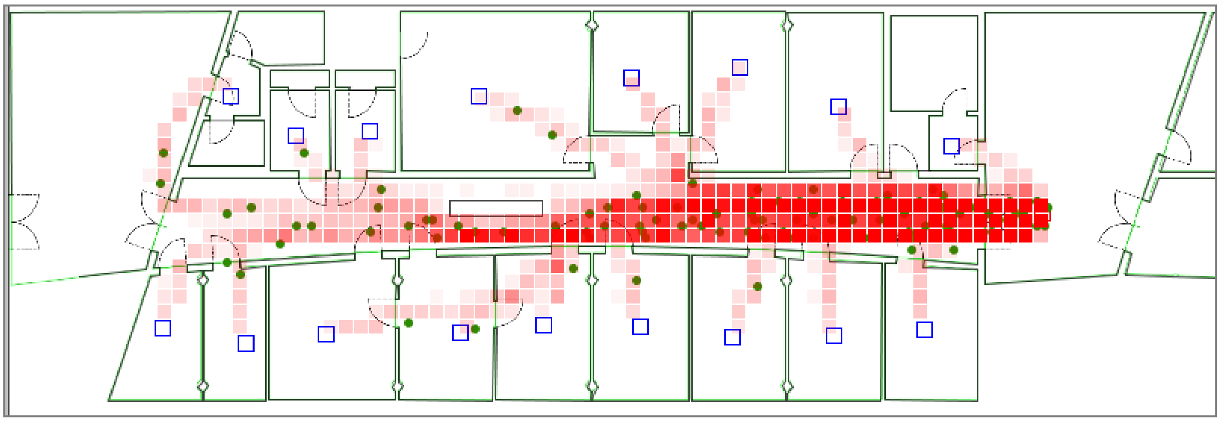

Figure 4: Simulation of the scenario modified by adding a display case in the main floor.

4 Image sequence-based analysis for enriching pedestrian behaviour maps

The image sequences or videos taken by surveillance cameras are analyzed to detect and track the pedestrians to improve the simulation model. Vision-based crowd analysis dealing with detection, tracking, occlusion handling, crowd modelling and event inference is still an unsolved problem, e.g. (Hu et al., 2004; Jacques et al., 2010). In particular, much work remains in the complex field of behaviour analysis in unstructured and changing environments (Dee and Velastin, 2008).

The strategy for vision-based pedestrian surveillance is split into two parts: first, single people are detected at the borders of the surveillance area and, second, these people are tracked through the following frames of the image sequence. The applied methods start with a simple blob detection if a pedestrian is defined with only few pixels in the image, e.g. (Schmidt & Hinz, 2011).The following tracking approach is accomplished with particle filters to enable non-linear movements of the pedestrians (Isard & Blake, 1998). The derived trajectories of the pedestrians are now used to enrich the pedestrian behaviour maps.

Event detection using extracted trajectories of pedestrians has been realized by several approaches, e.g. (Oliver et al., 2010; Nascimento et al., 2010). A basic method for the analysis of those trajectories are Hidden Markov Models (HMM) (Rabiner, 1989), which serve for further trajectory analysis. We aim at modelling the behaviour of larger groups of people interpreting their interaction using tracked pedestrians and simulations as input information. Behavioural maps provide important input data for event detection systems, because simulations enable easily modifiable training sources, if real-training data is not available to learn the motion patterns defined in the HMM.

Starting point of the event detection is a dynamic pedestrian graph constructed with the trajectories of all tracked pedestrians in the investigated environment. The HMM-based analysis of the edges in the graph is performed to derive statements of the motion interaction between pedestrians (Burkert et al., 2010; Burkert et al., 2011). In a first step, the HMM is learned offline from real-world training data of the scene of interest containing recurring trajectories. However, if not available, simulation data can be used instead for the training. As a result, pre-defined events are detected and can be used to improve the pedestrian behaviour maps.

5 Inertial measurement-based tracking for enriching pedestrian behaviour maps

To gain finer grained information on pedestrian movement patterns, Inertial Measurement Units (IMU) are used to monitor step characteristics, speeds, accelerations and direction changes. Up to now we have developed foot mounted and pocket based sensor prototypes that are able to continuously track the movements of a pedestrian. Figure 4 shows the components of the current pedestrian tracking system.

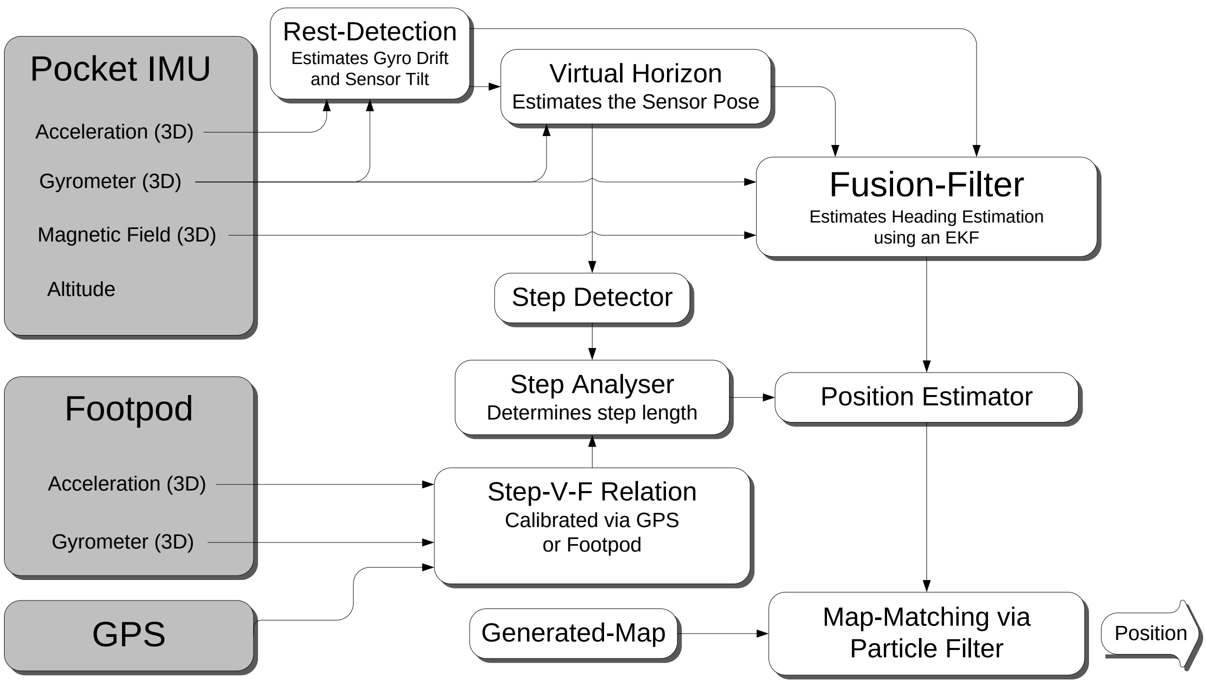

Figure 5: IMU based individual tracking system

Calibration data are collected via the GPS and the Footpod Unit to automatically determine a user’s step profile. The step profile gives an estimation on the users physiological step-frequency/speed relation. With this relation a detected step-frequency can be transformed into a step-length estimation that is used for position updates.

When the step-profile is complete the user can be tracked using only the pocket mounted sensor. The sensor's data is first used to determine the user's state (whether he is resting or moving). In the latter case the data is used to establish a virtual horizon of the user's movements. The horizon filter enables the system to remove the movement artifact introduced by the periodic hip oscillations during walking. Via the succeeding fusion filter the user's current orientation is merged with a forward movement when a new step is detected via a step analyzing unit. The orientation is fused together with the distance update in a map matching particle filter. In this filter illegal position updates, such as updates traversing a wall are deleted and the plausible position updates are propagated. Hence the particle filter constantly produces individual position updates. When several users are equipped with the described sensors, the tracking data can be collected at a central server. Server based algorithms can then be used to extend an existing map with temporal movement patterns. The sum of these patterns indicates reachable regions of the map and the density gives a hint on the utilization of a certain area. Together with the temporal information time dependent utilization scenarios can be stored in the resulting map.

6 Resulting enhanced behavioural behaviour map

After incorporating the tracking information from both sensors systems, the resulting pedestrian behaviour map contains improved information on pedestrian movements in high spatial and temporal resolution.

The enhanced behavioural map can be seen as a "three-layered" information source. Layer 1 contains the topography of the scenario as given by ordinary building plans. Layer 2 enhances this topography by indicating paths frequently followed by pedestrians as well as regions that are scarcely visited. These scarcely visited areas give hints on obstacles that are not depicted in Layer 1. On the other hand it reflects the behaviour of people visiting a building. The third layer refines this behavioural information by describing temporal movement streams and distilling probabilistic descriptions of interaction events.

Such an enhanced behavioural map forms an improved basis for performing pedestrian simulations, since on the one hand it implicitly contains also the obstacles and attraction points not represented in the initial floor plans, and on the other hand it describes their evolvement and influence on pedestrian movements over time. Moreover, behavioural maps link spatial zones with pedestrian behaviour patterns (waiting, slow motion, etc.) as well as pedestrian interaction patterns (meeting, separation, etc.). The knowledge of the spatio-temporal distribution of these patterns forms an important input for the pedestrian simulation, resulting in improved accuracy of the predicted behaviour.

In addition, behavioural maps provide important input data for pedestrian tracking and event detection systems: For event detection, simulation runs based on the proposed map provide easily modifiable training sources. For example, frequently used Hidden Markov Models for the automatic interpretation of the detected trajectories (e.g. event detection) can be trained or tested against simulated data. Also for tracking applications, the resulting maps are highly beneficial since the different layers allow the formulation of tighter bounds for filtering mechanisms (e.g., paths frequently used in the past are also more likely to be taken in the future).

Finally, pedestrian behaviour maps serve as a suitable basis for comparing simulation results with real-world data gained using tracking and event-detection technology, thus enabling the validation of the simulation system.

7 Summary and Conclusion

This paper presented the concept, creation and use of pedestrian behaviour maps which describe the movements and interactions of individuals in a given spatial scenario. These maps are created starting from a static floor plan, continuously enriching it by dynamic data gained through computational pedestrian simulations as well as real-world tracking and event detection data.

The resulting map defines not only the spatio-temporal evolvement of primary pedestrian stream characteristics, such as mean velocities and densities, but also aggregated trajectories as well as zones of typical pedestrian behaviour (waiting, slow motion, etc.) and typical pedestrian interactions (meeting, separation, etc.). On the one hand, this advanced pedestrian behaviour information provides more detailed input for improving the accuracy of both, pedestrian simulations as well as tracking applications. On the other hand, it serves as a suitable basis for comparing simulation results with real-world data, thus enabling the validation of the simulation system.

In the future, the authors of this paper will continue collaborating to realize the concept of multi-layer pedestrian behaviour maps and prove its advantages for various application domains.

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