

MAPS AND FLOOR PLANS ENHANCED 3D MOVEMENT MODEL FOR PEDESTRIAN NAVIGATION

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ABSTRACT

Pedestrian mobility models are becoming essential in several technologies and techniques. Applications of these models could be found in the areas of infrastructure design, evacuation planning, architecture, robot-human interaction, pervasive computing or navigation and localization. Within the scope of this paper, the purpose of such models is to realistically represent the stochastic nature of pedestrian's movement. Our aspiration is to generate a "movement" or transition model for positioning systems that are based on sequential Bayesian filtering techniques, such as particle-filtering [AMGC02] [GSS93]. However, the developed models can be applied to many of the above application domains.

In this paper the three dimensional pedestrian movement model presented in [KKRA09] is extended in order to make use of the valuable prior knowledge of maps of the surrounding environment. The result is a three dimensional mobility model that is capable of representing pedestrian movement in challenging indoor and outdoor localization environments. Examples of such

environments are multi-floor buildings, streets, ways, meadows, coppices and forests. Additionally, some quantitative and qualitative analyses of the model and the improvement it brings to the overall positioning performance will be illustrated.

The model actually consists of two movement models, operating at the microscopic level and suitable for pedestrian navigation. The constituents are a Three Dimensional Stochastic Behavioral Movement Model (3D-SBMM) to characterize random motion, and a Three Dimensional Diffusion Movement Model (3D-DMM) to characterize geographical goals a pedestrian might walk towards. In order to account for the fact that humans might switch between a goal-directed motion and a stochastic motion, a top-level Markov process is designed to determine when to switch between the 3D-SBMM or the 3D-DMM. Both models use the a priori knowledge of maps and floor plans.

The designed model is implemented, tested and evaluated in an already available distributed simulation and demonstration environment for mobility, localization and context applications.

The benefit of movement models in the framework of dynamic positioning estimators and a summary of related work will be discussed in section 1. The three dimensional movement model, its constituents, properties and computations will be explained in details in section 2. The question of "Can maps and floor plans replace a proper movement model?" is discussed in section 3. System design and implementation will be illustrated in section 4. Experimental results will be given in section 5. Finally, some conclusions and future work will be given in section 6.

1. INTRODUCTION

1.1. MOVEMENT MODELS & DYNAMIC POSITIONING ESTIMATORS

Dynamic indoor and urban canyon navigation are application areas that are becoming increasingly important. Efficiency, reliability and accuracy of these applications can be improved if appropriate movement models combined with the knowledge of maps and floor plans are used.

The reason that a movement model is needed lies in the dynamic nature of most pedestrian indoor localization applications, where the user's position will be estimated continuously. Moreover, a dynamic positioning system is more accurate than a "single-shot" static estimator which essentially provides a position estimate based on positioning measurements at a single time instance.

An accurate and realistic movement model (known as the a-priori state transition model) of the dynamic system is needed to implement a mathematically reasonable dynamic positions estimator. We have grounded our work on the formalism of sequential Bayesian estimators, of which the well known Kalman Filter is a special case [AMGC02]. Basically, a sequential Bayesian estimator updates an estimate of a system's state over the course of time, given a set of new observations at each time instance. The estimator thus incorporates the new observations with all previous ones. But in order to do so correctly, it needs to include the possible changes of the system's state from one time instance to the next. This can be done through the use of movement models. Essentially, the more "predictable" the system state transitions are, the more the measurements can be filtered over time. Additionally, if measurements happen to be unavailable for one or more time steps, the movement model will still yield a prediction of the state estimate. Dead-reckoning essentially builds on this principle whereby the underlying movement model is very simple.

Better movement models will of course increase the accuracy of these dynamic estimators. For the pedestrian case, movement parameters like position, velocity, attitude, etc. are modeled. With the additional knowledge of maps, the movement model will result in a pedestrian who is not crossing walls, walking faster in open areas, walking slower in undulating terrain or with obstacles, not entering restricted areas and who is attracted toward points of interest, etc. Such prior knowledge enhances the model and improves its performance.

The map-enhanced movement model presented here is used to generate a probabilistic distribution of the system's states over the course of time. It is used in the framework of a dynamic location and direction sequential estimator that uses particle filtering as the fusion engine. Additionally, it is used in simulation and validation of indoor positioning systems by allowing us to simulate realistic pedestrian traces, and applying these traces as the controlling parameters of a system that simulates sensors such as indoor GNSS receivers and compasses.

1.2. SUMMARY OF RELATED WORK

Pedestrian movement models are used in the literature to represent the stochastic nature of pedestrian movement [Hel92a] [Tek02] [OkM93]. Interest might vary among different forms of pedestrian movement models according to the application. For example, in navigation; a detailed model of pedestrian behavior is of interest, while in pedestrian groups modeling; only statistical measures might be of interest.

1.2.1. CLASSIFICATION OF MOVEMENT MODELS

Pedestrian movement models are often categorized by the type of moving objects used to represent the persons to be simulated. There are mesoscopic models, macroscopic models and microscopic models [Hel92a] [Tek02].

At the **mesoscopic** level it is sufficient to describe the pedestrian movement models using approximate equations for the mean values of velocities as a function of some parameters like the pedestrian's age or activity [HSBP00]. Mesoscopic modeling was primarily made for traffic simulations, but later applied to pedestrian modeling.

Sometimes it is the case that further quantities describing the velocity probability density (typically the mean velocity and velocity variance) of pedestrians are of interest. In such cases fluid dynamic equations [Hel92b] are used to model the human behavior – this is denoted as **macroscopic** pedestrian modeling. The origins of these models are the gas-kinetic equations and they evolve from transportation modeling. The root of these models is the continuum model by Lighthill and Whitham (1955) [Add05] which solves differential flow equations.

At the **microscopic** level every pedestrian is treated as an individual agent who occupies a certain space at a certain time; then the interaction between the pedestrians is observed. There exist several analytical models that try to describe the microscopic behavior of a pedestrian, but with formulations that are difficult to solve. Accordingly, they are approached using Monte Carlo Simulations known as Microscopic Pedestrian Simulation Models (MPSMs). "Agent Based Models" is another terminology that is used in the literature to refer to microscopic models. Monitoring individual pedestrian's behavior can lead us to general characteristics regarding group behaviors such as the behavior in queues and the generation of freely-forming groups [Hel91].

In the pedestrian navigation domain, the microscopic description is the category of interest. They also have practical applications in evacuations planning, designing of pedestrian areas, and as an experimental & optimization design tool. A closer look to the work done at the microscopic level will be given next since pedestrian navigation is our area of application.

1.2.2. MICROSCOPIC MOVEMENT MODELS

Intentions and interactions of a pedestrian movement are of interest at all levels of description of pedestrian movement models.

Major microscopic pedestrian simulation models that could be found in the literature are Benefit Cost Cellular Model [Res04] [Tek02], Cellular Automata Model [YFL+03] [WLF03] [DJT01], Magnetic Force Model [OkM93], Social Force Model [HeM95] [LKF05] and Queuing Network Model [MaS98] [OsB07].

Our three dimensional movement models addressed in this paper can also be added to the above models.

1.2.3 MAP MATCHING

Map matching [BPWR05] [Sco94] in general is the concept in which tracking data and movement models are related to maps. The overall objective is to increase the accuracy of positioning using the knowledge that the tracked object is restricted in movements according to the map. With the aid of map matching navigation services can be improved.

Map matching can happen in real-time or offline according to the application. In the real-time scenario only the current and last-but-one position measurements are available. On the other hand, in the offline scenario some or even all position measurements are available.

There are two different types of map matching; “Classical Map Matching”, and “Movement Model Based Map Matching” [KSR07].

In *Classical Map Matching*, the objective is to improve the location estimation by snapping the measurements to the nearest path (polyline) in the map. The standard approach of Classical Map Matching is the Incremental Method [BPWR05], in which an incremental match of the position measurements to the road network points is done. Another approach is the Global Method [BPWR05], in which curves in the road network that are as close as possible to the measured trajectory are searched and matched. The basic four steps of Classical Map Matching are illustrated in [TTC04].

In *Movement Models Based Map Matching* [KSR07], the map is used to restrict the probabilistic movement of the tracked object. Accordingly, the tracked object will only move in allowed areas.

Different kind of maps and several levels of abstraction can be used in Movement Model Based Map Matching according to the tracked object. Examples of such maps are roadmaps, topographical maps and floor plans. For example, with the knowledge of a floor plan, the pedestrian will not be allowed to cross walls. Additionally, through the knowledge of geographical maps, the speed of the pedestrian might be governed by the presence of obstacles and terrain steepness.

2. A COMBINED 3D-DMM AND 3D-SBMM

The Diffusion Movement Model is well suited for a goal-oriented movement, while the Stochastic Behavioral Movement is well suited for a non-goal-oriented movement [KKRA08]. Details of our work toward extending both models into 3D and the approach to combine them in order to cover both types of movement will be given next.

2.1 THREE DIMENSIONAL STOCHASTIC BEHAVIORAL MOVEMENT MODEL (3D-SBMM)

Pedestrian mobility at the kinematical level is characterized by physical parameters such as speed and direction of motion. The knowledge of speed and direction combined with the elapsed time can be used to

calculate the new pedestrian position. However, speed and direction are affected probabilistically by several hidden states. These states are human parameters that identify his situation such as age, pursued activity, emotions, degree of disorientation and age or other non-human parameters that affect his situation such as weather, obstacles and time of day. Accordingly they can be categorized into human and non-human movement constraint states.

Movement constraint states can also be categorized into two groups using another methodology. The first category includes states that the system can find out accurately such as age, weather, time of day and states that can be derived from external data like ground steepness or obstacles at the pedestrian’s position. The other category includes states that are varying according to the human behavior. In general it is not simple to determine straightforwardly states falling into this category. Examples of these are pursued activity, disorientation, and other emotional or cognitive states.

To illustrate the importance of these states in defining the pedestrian movement some examples will be given next:

- It is more usual for a disoriented pedestrian to walk irregularly compared to somebody who is walking a familiar route.
- At some specific times of the day and weekdays the pedestrian might tend to move slower. Additionally, the knowledge of the time of the day and the weekday can be used to predict the pedestrian activity which directly affects the speed calculation (this can be particularly important in evacuation planning or in situations where the density of people varies strongly).
- A pedestrian running to catch a train is faster in general compared to another pedestrian who is window shopping.
- The pedestrian cannot penetrate a wall under any normal circumstances. It is important here that we have to consider in the design that some of these parameters affect the movement more than others. Building layouts are obviously amongst the main parameters that strongly constrain the movement of the pedestrian.
- Some special kind of activities such as rolling, jumping and climbing, result in some special kind of movement.

In our approach the second category variables are modeled in a simplified fashion using Markov processes. The idea of using Markov Chains for describing human behaviors could also be found in [PeL99], [ZhN02] and [AdA04]. The transition probabilities of these Markov chains are set according to statistics and a-priori assumptions that are rooted in common sense.

We have explained in detailed our design of a two dimensional Behavioral Movement Model in [KKRA08], [WKAR06] and [Khi05]. In order to add the third dimension to the designed model, the speed and direction models are also constructed in the Z-direction. With this extension we are able to probabilistically predict

pedestrian movement as a function of behavioral parameters in X, Y and Z-directions at every time step. Speed and direction are designed to be a function of:

1. Parameters that affect the human movement such as age and activeness. The same eleven parameters in [KKRA08] are considered.
2. The building geometry and the stairs type play an important role in building the Z-direction part of the model.
3. The previous speed in X, Y and Z- directions.

It is important to note that movement in Z-direction is connected strongly to movement in X and Y - directions. For example, a pedestrian who is moving very fast in X, Y- directions might not be able to keep his X, Y- speed if he starts additionally moving in the Z-direction. On the other hand, if the pedestrian enters a stairs area with a high speed in X and Y, then his initial vertical speed will also be high.

Whereas this model is based on real statistical data and capable of representing movement well in situations without external constraints, it is not suited for situations in which walls or roads have a strong influence on the movement. This model leads to a high probability of getting stuck in a room or having problems in getting through narrow openings and sharp turns [KKRA08]. This is due to the random movement that the model follows which does not react to the presence of a door, a narrow opening or a sharp turn. Additionally, the model does not include the behavior of a pedestrian heading towards a specific destination.

2.2 THREE DIMENSIONAL DIFFUSION MOVEMENT MODEL (3D-DMM)

The 3D-DMM is an extension of the 2D diffusion movement model demonstrated in [KKRA08]. This model is derived from the principle of gas diffusion in space studied in thermodynamics and is a standard solution for path finding of robots [ScA93]. The idea of this model is to have a virtual source at a certain location continuously effusing “gas” that disperses in free space and which gets absorbed by walls and other obstacles [KAL03]. To reduce the computational effort, we project the 3D environment into a Quasi-3D-Environment that is described in section 2.2.1. Section 2.2.2 describes the computation of the diffusion matrix and section 2.2.3 handles the methodology to calculate the appropriate Z-position in the Quasi-3D-Environment. Considering additionally maps in the 3D-DMM will be explained in section 2.2.4 and, finally, advantages and disadvantages of the model are described in section 2.2.5.

2.2.1 PROJECTON OF THE 3D ENVIRONMENT INTO A QUASI-3D- ENVIRONMENT

Many of the indoor environments have more than one storey or floor. In such cases, it is necessary to consider several floor plans and accordingly different heights (Z-direction). For the 3D-DMM this means that the gas will flow in three dimensions, but this would be unrealistic for

a human motion model since motion does not follow the third dimension freely. Since a normal pedestrian will walk on the ground of a floor, the 3D environment – including stairs - can be projected into the 2D projection domain.

For projecting the floor levels just the 2D floor plans can be taken like in the 2D environment. Additionally, the stairs areas should be handled separately: For projecting the stairs into the 2D area one needs the 2D top view of the stairs.

There exist different kinds of stairs: stairs with and without pedestal, dog-legged stairs and newel stairs. All kind of stairs share a common feature which is the possibility to project them into 2D area(s). Difficulties for computing the diffusion matrix arise in the stairs area, because of the change in the ground height at each step and the different connection of the exit and entrance of the stairs to the respective layer. The procedure of handling this special area while computing the diffusion matrix is described in the following section.

2.2.2 COMPUTATION OF THE DIFFUSION MATRIX

The computation of the diffusion matrix for the 2D environment is extensively described in [KKRA08]. To keep the model’s complexity low, the 3D-DMM is confined to rectangular areas representing different floor levels. For such rectangular area a set of destination points has to be specified, where each destination point represents a source effusing gas. This destination point can be seen as the most important free variable in our model: for a probabilistic model this can be chosen randomly and change from time to time; in a scenario where we model human behavior when a person moves to a certain known destination we just set the destination point appropriately. For each destination point a so called diffusion matrix is pre-computed by applying a filter. The diffusion matrix for a particular destination point contains the values for the gas concentration at each possible waypoint when gas effuses from that destination point. The path is computed by backtracking from the destination point towards lower values of the diffusion matrix until the current waypoint is reached.

According to the gas diffusion principle in 3D, the gas will flow between floors using the stairs. Thus, when calculating the diffusion matrix for a specific floor, the diffusion matrix of the stairs area of the upper and/or lower floors has to be considered. And since the stairs are always connected to two different levels and its diffusion matrix will affect the diffusion matrix calculation of both layers, one has to consider each stairs area as a separate layer. Each layer of the stairs is the projection of that stairs in 2D. So for example, to compute the diffusion matrix for the 3 level building shown in Figure 1, one has to consider 3 floor plans and 2 plans for the stairs between the levels (we call it $x \frac{1}{2}$ level).

For computing the diffusion values of each floor, we first integrate the respective stairs area into the floor plan of the respective level. Integration of a stairs area means

that the projected stairs area is included in the floor plan of a level. Then, we compute the diffusion matrix for each level separately.

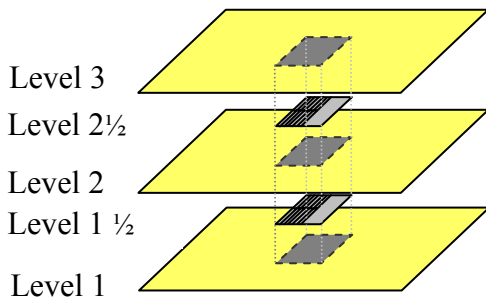


Figure 1: A building with 3 levels and two projections of the stairs (“x ½ level”)

We classified floors into two types that will be considered differently during the diffusion process:

- A floor that is connected to other floors but with the connecting stairs areas in different X-, Y-locations. This means that the projection of the connecting stairs areas do not overlap or lie on top of each other in the projection domain. A floor that is connected to only one other floor belongs also to this category (level 1 and 3 in Figure 1).
- A floor that is connected to other floors with the connecting stairs areas at the same location (level 2 in Figure 1). This means that the projections of the connecting stairs areas lie on top of each other or overlap in the 2D projection domain. In this case the diffusion matrix of this floor has to be computed for each of the two different stairs areas (level 1 ½ and 2 ½ in Figure 1).

Since the area of the stairs is projected and there are no walls at the entrance and exit of the stairs, we have to introduce a virtual wall that prevents the gas from flowing through the not connected entrance or exit at the same time if we integrate the stairs area in a floor plan. The concept with the virtual wall is introduced to let the gas correctly flow into the next level through the valid connecting area. In addition, in the case of two reachable staircases as in level 2, with the virtual wall one can distinguish between the stairs going upstairs and that going downstairs.

The following pseudo-code describes the diffusion process for a building with several levels:

```

for (i=0; i < imax; i++){
  for (n=0; n < Nb_of_levels; n++){
    integrate all non overlapping
    stairs of level (n+1/2) and (n-
    1/2) in level n

    if (stairs overlap){
      integrate overlapping stairs
      of level (n-1/2) in level n
    }
  }
}

```

```

apply Diffusion Filter on level n

  if (stairs overlap){

    integrate overlapping stairs of
    level (n+1/2) in level n

    apply Diffusion Filter on
    level n

  }

}

```

Here, *imax* is the maximum number of iterations the diffusion filter is applied and *Nb_of_levels* is the number of different floor levels. The diffusion filter is iteratively applied for all floor levels. The diffusion filter is applied twice for floor levels that are connected to overlapping stairs or stairs that lie on top of each other. The virtual wall is included while integrating stairs.

The filtering algorithm for computing the diffusion matrix will reach the steady state after several iterations and, therefore, calculating the diffusion matrix for level 2 twice in one 3D iteration step will not affect the diffusion results.

It should be noted that if the diffusion matrix values of one stairs area are changed, they are changed also for all the integrated (same) stairs areas in other levels. Additionally, any change of the values of that stairs area will have an influence on both levels since the stairs area is situated between two levels and is connected to both of them. This will ensure the flow of the gas in both up and down directions and that is important in the case where there are more than one stairs areas in a building.

According to the above mentioned algorithm, one iteration of the diffusion process for a three floor building consists of three steps that can be seen in Figure 2. Because layer 2 is connected to two stairs areas the computation of the diffusion matrix is done twice: first with integrated stairs area 1 ½ (Step 2a) and secondly with integrated stairs area 2 ½ (Step 2b). Additionally, the virtual wall can be seen as a blue line in Figure 2. The virtual wall is added at the exit/entrance that is not connected to the respective layer. More explanation could be found in [KKRA09].

The area under the stairs in level 1 is not considered in our computations, because it is very improbable, that a person is crawling rather than walking under the stairs. But if it is possible to walk in the area below the staircase, the diffusion for this area could be similarly computed in two steps like in level 2, step 2.

2.2.3 CALCULATING THE Z-POSITION

A methodology to calculate the position in the Z-direction at every time step is to generate a matrix that contains for every (X, Y) coordinates a relevant Z-coordinate. In this case the knowledge of X and Y positions will be enough

to return the appropriate Z. With the projection of the stairs into the 2D area, the information of the Z-position can be appended: For each step area of the staircase a different Z-value can be stored. This means, that the Z-position is stored for different areas: The different floor-level areas and the different areas for each step of the staircase have different heights, respectively.

2.2.4 MAPS HANDLING

In this section we will describe the extension of the diffusion movement model for handling maps in indoor and outdoor environments. Maps contain useful information that influences pedestrian movement such as the different types of areas which have different degree of accessibility. Examples of these areas are forests, fields, streets, ways, meadows, coppices, flowerbeds, houses, walls, etc.

Typically, persons do not walk through forests, fields, coppice, flowerbeds, etc. Meadows are more accessible for kids or in sunbathing areas. Furthermore, most probably persons do stay on ways or streets (on the pedestrian sidewalk). Walls are not accessible, whereas houses could be entered through doors. Inside houses, floor plans are active, but also maps could be considered: The areas with non accessible furniture stands (tables, cupboards, etc.) are not reachable. On the other hand, chairs are accessible. Therefore, the idea is to apply the diffusion movement model including maps, indoor and outdoor where different accessible areas can be handled differently.

For handling the degree of accessibility we have to modify the layout map matrix which is considered in the computation of the diffusion matrix. The new layout map matrix **L** is defined as:

$$l_{i,j} = \begin{cases} \frac{1}{v} & \text{if } l_{i,j} \text{ is accessible, } v=1..255 \\ 0 & \text{if } l_{i,j} \text{ is not accessible} \end{cases} \quad (3)$$

$\forall i, j: i=0, \dots, N_x, j=0, \dots, N_y$

where $N_x \times N_y$ is the size of the rectangular area. For inaccessible points (e.g. walls and closed areas) the values of the layout map matrix are set to zero. For the accessible areas the layout map matrix will have different values depending on the accessibility. The most accessible areas will have a value v of 1 whereas the least accessible area will have a value v of 255. According to the accessibility of a specific area the values v lie between 1 and 255. The values lie between 0 and 255 following an 8-bit PCM-representation. This representation was selected since it provides a reasonable range in the diffusion matrix.

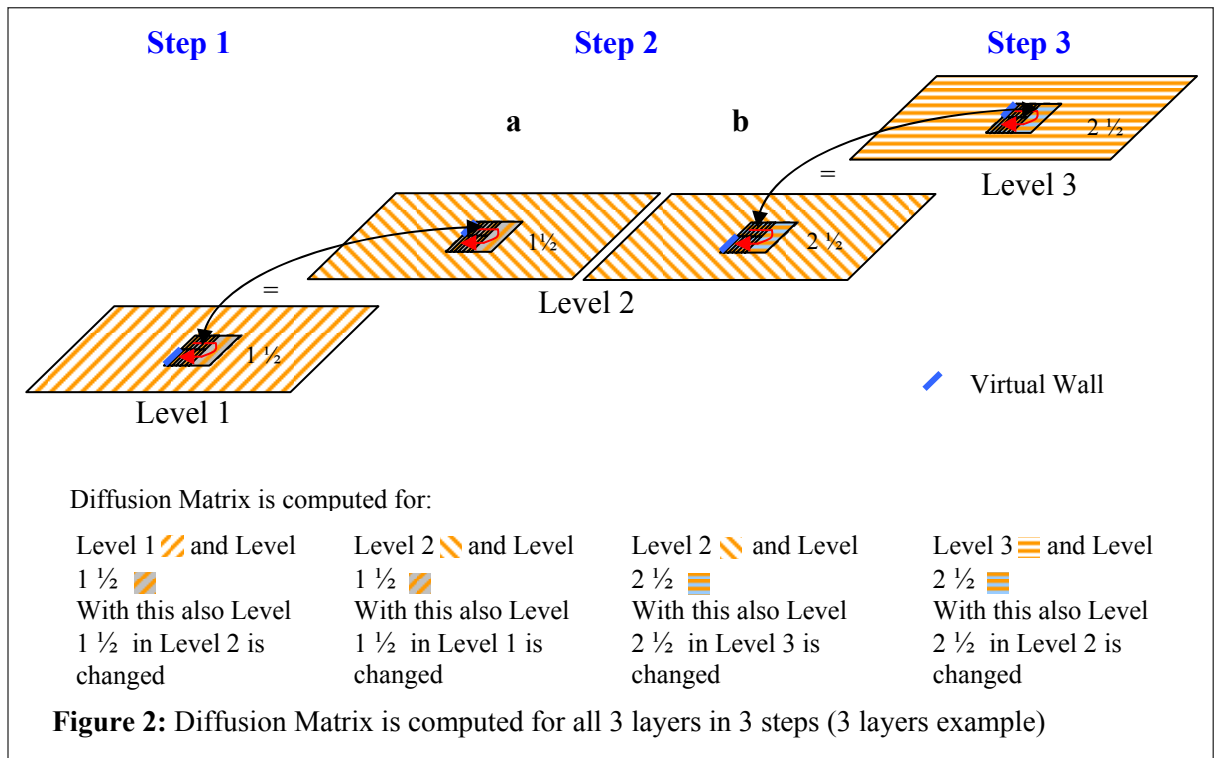
The diffusion process with these new defined values of the layout map matrix is as follows:

$$W_m(x_m, y_m) \in \mathcal{W} \quad (1)$$

First, for the rectangular area a set \mathcal{W} of N_w destination points $\{(x_1, y_1), \dots, (x_{N_w}, y_{N_w})\}$ has to be specified, where each destination point represents a source effusing gas. For each destination point a so called diffusion matrix **D_m** is pre-computed. The diffusion matrix for a particular destination point contains the values for the gas concentration at each possible waypoint assuming that the gas has effused from that destination point. For this, a filter **F** of size $n \times n$ is applied:

$$f_{p,q} = \frac{1}{n^2} \quad \forall p, q: p, q=0, 1, \dots, n \quad (2)$$

The diffusion is expressed by a convolution of the diffusion matrix **D_m** with the filter matrix **F** element-



wise, multiplied by the layout map matrix L :

$$d_{i,j}(k+1) = l_{i,j} \cdot \sum_{p=1}^n \sum_{q=1}^n d_{i+p-1,j+q-1}(k) \cdot f_{p,q} \quad (4)$$

Here, the l values represent a weighting of the diffusion values according to their accessibility.

Constantly refreshing the source is represented by forcing

$$d_{x_m,y_m} := 1 \quad (5)$$

at the destination point. Equation (4) is evaluated repeatedly until the entire matrix is filled with values that are greater than zero (except for walls and closed areas):

$$d_{i,j} > 0 \quad \forall i,j : i = 0, \dots, N_x, j = 0, \dots, N_y \quad (6)$$

The path is computed by backtracking from the destination point W_m towards lower values of the diffusion matrix until the current waypoint is reached.

Figure 3 shows a graphical representation of the layout map matrix for a scenery with two ways (white), a closed building (dark gray walls), fields (light gray) and coppice/trees (dark gray). A graphical representation of the diffusion matrix for that layout with a destination point in the field is given in Figure 4. Destination points are represented by red dots in our figures. The gas concentration is high in the dark red area and low in the blue area.

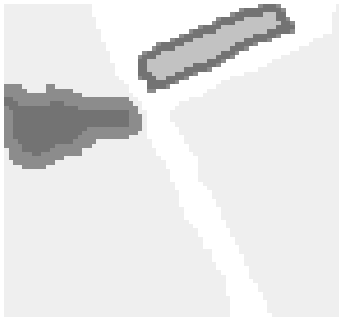


Figure 3: Layout map matrix

From Figure 4 one can see that the person coming from the way will be walking further on the way and then going to the destination point situated on the field. She is not using the shortest way due to the given layout map matrix. This is comparable to the human behavior, since it is more convenient to stay as far as possible on the way.

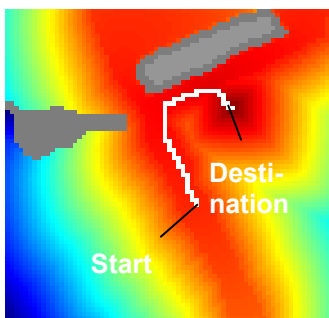


Figure 4: Diffusion matrix and trace for a starting point on the way

Figure 5 shows the trace for a starting point on the field. The person goes on the street and follows it until the shortest way to the destination point from the street is reached. If the destination point on the field is very close, then the path would be the direct one over the field.

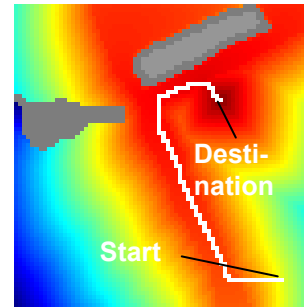


Figure 5: Diffusion matrix and trace for a starting point on the field

Figure 6 shows the layout map matrix adequate for our office environment. The walls are given in black, not easy reachable forest area is marked with dark gray, and flowerbed area is given in light gray. The area where people may walk is given in white. Additionally the stairs area is marked in blue and again red dots are possible destination points. No destination points can be located in black and dark gray areas. The diffusion result for one layer is given in Figure 7. One can see that gas coming from the destination point in the left down corner effuses faster in the white areas (dark red color) and slower in the dark gray areas. Additionally, gas will not flow in closed rooms of the building.

By using maps one can easily handle restricted areas such as forests, walls, etc. In addition, one can precisely define areas where a person may stand and where not, both in indoor and outdoor environments.

In order to reduce the computational effort during the run time, the diffusion matrix \mathbf{D}_m is pre-computed for all the destination points and the angles of the paths toward each of them are saved [KKRA08]. Since the destination point for the pedestrian is not known during runtime, the destination points are chosen randomly (assuming here a uniform distribution). The destination point is stored until it is reached, changed or if the 3D-SBMM is selected (see section 2.3).

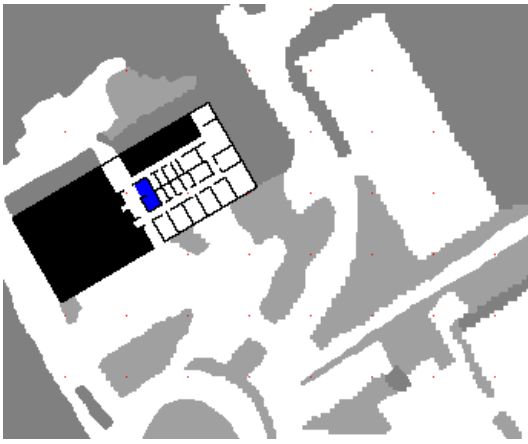


Figure 6: Layout Map for our simulation environment

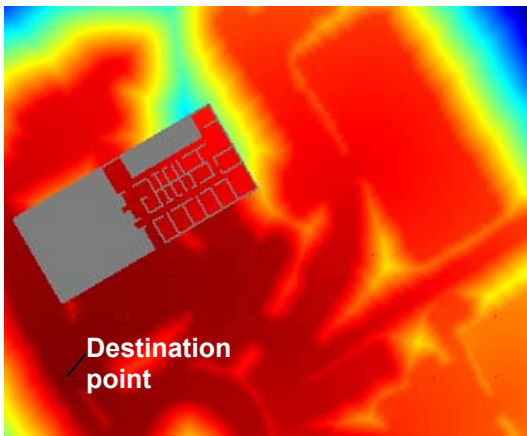


Figure 7: Diffusion matrix for our simulation environment

2.2.5 ADVANTAGES AND DISADVANTAGES OF THE 3D-DMM

With the 3D-DMM the pedestrian does not “get stuck” in rooms or fails to enter them. Additionally, a simulated moving person finds the exit of a room faster than with the 3D-SBMM, especially when the door opening is small. Furthermore, goal-oriented movement is included. A disadvantage of using the 3D-DMM is that if we assume that the destination point is not known then this true destination point may not be in or close to our set of destinations, so that the model is not able to capture the actually observed motion particularly towards the end of the true trace that is walked. Another disadvantage is that it does not model local random motion very well, such as when a person is not walking to some target – for example whilst walking around in an office talking to somebody. Additionally, a pedestrian does not always follow the shortest path. Therefore, a combination of both 3D-SBMM and 3D-DMM is proposed in our new model. We found that a combination of both models is particularly advantageous and will be described next.

2.3 THREE DIMENSIONAL COMBINED MOVEMENT MODEL

Both the 3D-DMM and 3D-SBMM have advantages and disadvantages. Our approach was to combine both models intelligently trying to obtain the advantages of both models and get rid of as much of the disadvantages as possible. The models are combined via an extended Markov model. The combined three dimensional model switches between motions that are non-goal-oriented (section 2.1) or goal-oriented (section 2.2) with a small transition probability. Details on such combined movement model can be found in [KKRA08] [KKRA09].

The previously illustrated 3D-DMM does not include a speed model. Accordingly, if the pedestrian switches to a targeted movement, the 3D-SBMM will still be used to model the speed and accordingly the distance at every time step. The diffusion model effectively determines the heading that is followed.

2.4 THREE DIMENSIONAL POSITION COMPUTATION

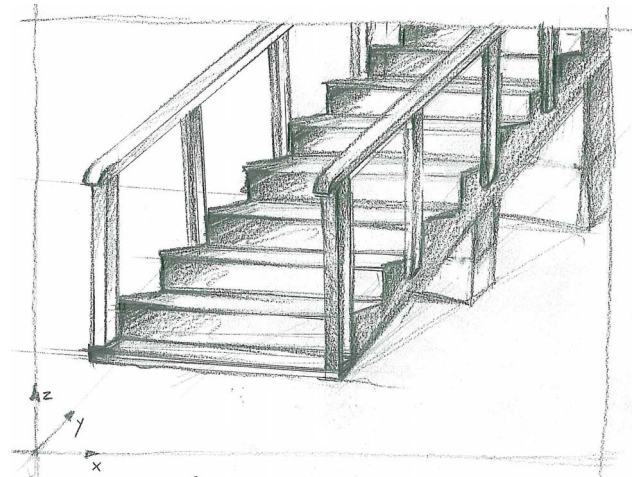


Figure 8: Coordinates of three dimensional stairs

For computing the 3D position the model continuously checks if the pedestrian enters any of the stairs areas in his current floor. While the pedestrian is outside the stairs area, the third dimension calculations are turned off since a normal pedestrian can walk only on surface areas. This saves us some computational costs. Additional computational costs are saved by only testing the stairs areas that are close to the pedestrian. If the pedestrian is detected to be in any of the stairs areas, then the third dimensional calculations in the current used model is turned on. Here, specific stairs area (Figure 8) considerations are applied. Examples of such considerations are the area geometry, the stairs type, and the activity of the pedestrian (walking up the stairs or going down). The side walls of the stairs are used to prevent our modeled speed of the pedestrian from resulting in a wall crossing movement.

The knowledge that the pedestrian has entered the stairs area heading up or down is essential. It will be used in calculating the pedestrian speed since the speed going down the stairs is faster normally than the speed going up. Additionally, it is used with the knowledge of the pedestrian's exit location to set the new floor level when detecting the pedestrian leaving the stairs area. We can easily check if the pedestrian has entered the side going up or down of the staircase with the knowledge of the building floor plan and his/her entry location. It has to be noted that the stairs area in the highest and lowest floors are accessible from one side only since each of them is connected to only one floor.

The extended Markov model will still be used to decide if the pedestrian in the stairs area is just walking around or targeting a goal somewhere up or down the stairs. According to the used 3D model (targeted or not-targeted) and applying the above stairs restrictions, the pedestrian's new position on the stairs can be calculated out of the old position and the elapsed time since the last calculated position.

After every computed position on the stairs, the pedestrian's new position is checked if it is still in the stairs area. If the pedestrian is detected leaving the stairs area the pedestrian floor level is either incremented or decremented according to the movement direction. Outside the stairs area the pedestrian will follow the 3D calculation will be stopped.

For simplicity, X and Y positions only are calculated at every time step, while the Z-position is retrieved using the methodology explained in section 2.2.3. Our pseudo-code formulation for generating a new three dimensional position is:

```

else {
  - Generate and return
  position by running the
  3D Combined Movement
  Model (see section 2.3)
  in 2D only. Special case
  since human walk normally
  on surface areas.
}
}
else {
  - Generate and return new
  pedestrian position on the
  stairs using the 3D
  Combined Movement Model
  (see section 2.3)
  - Check if the new pedestrian
  position is outside the
  stairs area:
  If (true) {
    - Increase, decrease or
    keep the old value of
    the pedestrian floor
    level depending on the
    "movement direction"
    variable and his/her
    exit location
    - Set "already in stairs
    area" to false
  }
}
}
}

```

```

Generate 3D position (old
position, timeDuration) {
  If ("already in stairs area" =
  false) {
    - Search staircases that are
    close to the pedestrian in
    the current floor
    - Check if the pedestrian is
    inside any of them:
      If (condition true) {
        - Check if the pedestrian
        enters the side going up
        or down of the staircase
        based on the floor plan
        and his/her entry
        location. Accordingly set
        "movement direction"
        variable to up or down
        - Generate and return new
        pedestrian position on
        the stairs using the 3D
        Combined Movement Model
        (see section 2.3)
        - Set "already in stairs
        area" to true
      }
    }
  }
}

```

3. CAN MAPS AND FLOOR PLANS REPLACE A PROPER MOVEMENT MODEL?

Several authors in the navigation community thought that the knowledge of maps and floor plans might be enough to probabilistically predict the movement of the pedestrian over time as in [KrR08]. In such implementations walls were hindering the movement and maps were deciding the most probable paths.

Such implementation of the pedestrian movement model will work only in special cases and will fail in many others. To illustrate that, we will consider the example of a Sequential Bayesian Positioning Estimator that is based on Likelihood Particle Filter (LPF). A LPF is a particle filter that is using measurements for drawing importance samples and transition models (movement models) for weighting the particles. Let's assume that at the beginning particles were distributed equally inside and outside a building since the starting position of the pedestrian is unknown. Additionally, we assume that the area outside the building is an open area where the pedestrian can walk everywhere.

First, we investigate the case of using only floor plans and maps for weighting (no proper movement model): particles that are inside the building will get good weights if they do not cross walls. Particles outside the

building will never get weighted as they do not cross walls and, therefore, they will also have good weights. For the case where the tracked pedestrian is inside the building only few of the particles inside the building will be following the pedestrian and at the same time not crossing walls (getting good weights). On the other hand, all the particles outside the building will have better weights since they are not weighted at all. Re-sampling will result in increasing the number of particles outside the building and decreasing the number of particles inside the building. This will result in divergence of the algorithm with time.

Secondly, we examine the case of using proper pedestrian movement models that incorporate the knowledge of maps and floor plans: particles inside the building will get good weights if they do not cross walls and follow the proper movement model. Particles that are outside the building will get good weights if they follow the proper movement model. For the case where the pedestrian is inside the building, measurements will be consistent with the normal pedestrian behavior inside rooms, corridors or stair areas. Accordingly, particles inside the building will get higher weights (measurements will be consistent with the movement model inside the building) compared to the ones outside the building (measurements will be inconsistent with the movement model outside the building). Re-sampling will result in increasing the number of particles inside the building and an improvement of performance and reliability.

The above example shows that maps and floor plans can improve movement models but not replace them. An optimal pedestrian movement model should do more than only incorporating maps and floor plans.

4. SYSTEM DESIGN AND IMPLEMENTATION

Some analyses of the added value of our developed three dimensional combined movement model on the overall dynamic positioning performance were required.

Sequential Bayesian Estimators are widely used in estimation problems that are related to noisy and heterogeneous sensors. Their ability to represent sensor outputs using probability density distributions (“soft estimations”) rather than providing point estimates (“hard decisions”) is a major advantage of these estimators. Without the use of the concept of probability densities, combining several noisy and heterogeneous sensors would have been difficult [ROAW02]. Another key advantage of such technique is the ability to include the system dynamics (mobility or movement models) in the estimation process. Through the use of movement models, floor plans, maps and human movement characteristics could be incorporated and as a result, more accuracy and availability could be achieved.

The developed model was tested and evaluated using an already available distributed simulation and demonstration indoor/outdoor environment for positioning. The environment is based on Sequential Bayesian Estimation techniques and allows plugging-in

different types of sensors, Bayesian filters and movement models.

Several ground truth points were carefully measured to the sub-centimeter accuracy using a tachymeter. The tachymeter employs optical distance and angular measurements and uses differential GPS for initial positioning. The Leica Smart Station (TPS 1200) was used for this purpose. A test user was equipped with a version of the above environment that is:

1. Based on two fusion engines running separately for comparison; a Particle Filter engine and an Extended Kalman Filter engine.
2. Having our 3D map and floor plans enhanced movement model integrated and used in the particle filter engine.
3. Having a simple random walk to be used in the Extended Kalman Filter (EKF) engine.
4. Using the following sensors: commercial GPS, electronic compass and a foot-mounted Inertial Measurement Unit (IMU) with Zero Updates (ZUPTs) [KrR08].

The test user was requested to walk through a specific path that is passing through several of our ground truth points. Whenever our user passed through one of the ground truth points, the estimated position was compared to the true position. Errors between the true positions and estimated pedestrian positions were recorded and visualized. Some results will be given and discussed in the next section.

5. SIMULATION RESULTS

In the evaluation example, the user started outside our office building passing by two reference points before entering the building. The user then made three rotations around the ground floor of our building environment before going outside again. In each of the rotations, the user was entering five offices (same five offices are repeated in each round). After the third rotation the user left the building passing by the same starting reference points outside the building.

The position error vs. time of both the PF and the EKF estimators is shown in Figure 9. From the Figure, we can see that the estimator which incorporates a proper movement model is having an average position error of 1.82 meters. On the other hand, the estimator that is using a simple random walk model has an average position error of 59.78 meters. We can also notice that the EKF estimator was having a noticeable low position error at the first two reference point. The reason is that the user was outside and the GPS coverage was still available. Additionally, we can see that the position error of the EKF estimator at few reference points later was still not very high. The reason is that the IMU and the compass measurements were still good enough to generate reasonable estimations. However, with time and due to the noisy measurements and the lack of an appropriate movement model, the EKF estimator starts diverging and the position error grows. At the time the pedestrian goes again outside the building, we can see that the EKF error

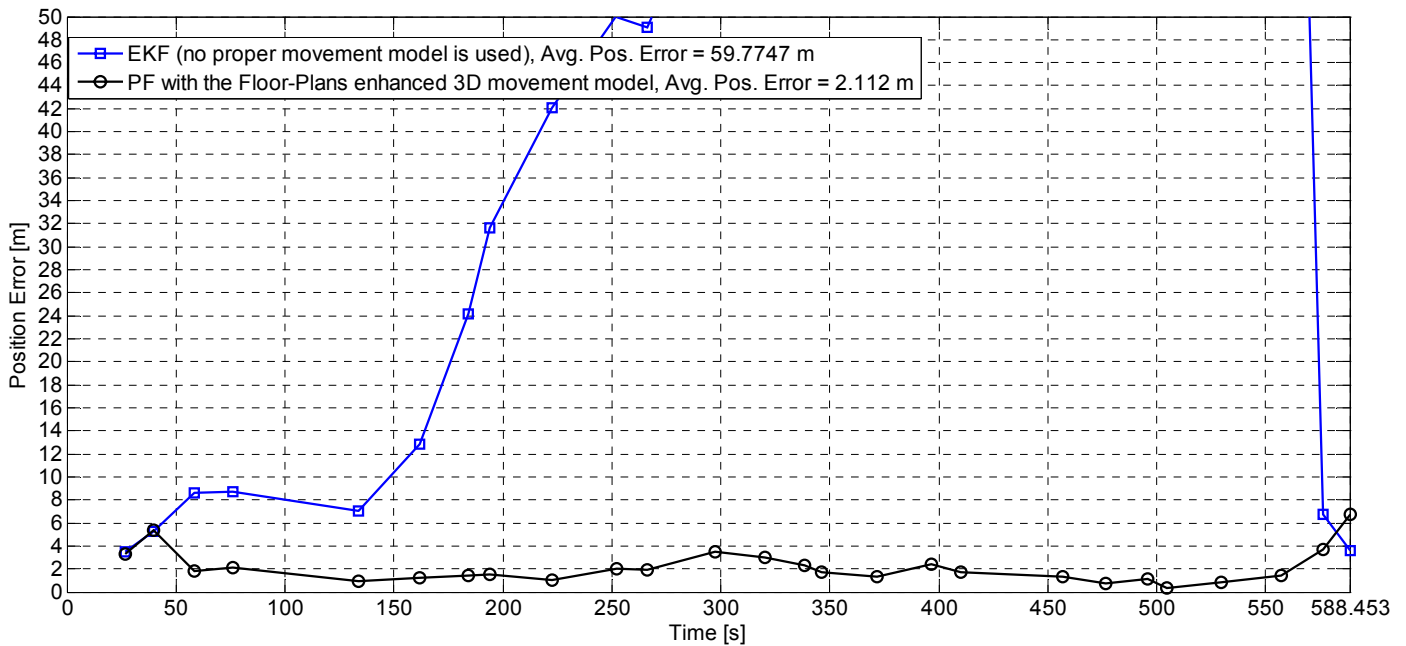


Figure 9: Position Error for a Particle Filter based Position Estimator (with a proper movement model) VS. Extended Kalman Filter based Position Estimator (with a random walk model)

goes down dramatically and this is due to the return of the GPS coverage and availability of accurate measurements accordingly.

On the other hand, the PF estimator continues to keep a small position error even in the case of noisy measurements. This is due to the use of a proper map and floor plan enhanced movement model. Figure 9 gives a clear indication of the performance improvement resulting from incorporating proper pedestrian movement models into positioning estimators.

From our performance analysis we have noticed that a proper movement model has made our positioning estimator more reliable. This can be shown if we introduce short disturbances to any of the sensors during the evaluation run. With the integrated movement models, any unrealistic sensor measurements will be excluded since they will be inconsistent with the movement model. As expected, positioning estimators that incorporate proper movement models are more resistant to short sensor disturbances.

6. CONCLUSIONS AND OUTLOOK

We have presented a human pedestrian motion model that accounts for targeted and untargeted motion in three-dimensional environments such as buildings that have stairs to connect different levels. Since human motion is restricted to surfaces we have essentially projected 3D motion onto the appropriate surface, be it a normal floor or the stairs. Each projected step area is having a different height. Our model follows a combination between a diffusion process to represent paths that humans typically take to reach a destination and a behavioral model that incorporate the effect of the pedestrian situation on his movement. When our motion model is applied in a sequential non-linear (Bayesian) localization scheme such

as particle filtering, the model is typically used in the “prediction step” where we draw from a suitable proposal density (our model). However as in the Likelihood particle filter, the model is used in the “update step” where we give appropriate weights to particles that are moved according to the measurements. The model could also be used to calculate shortest paths or to estimate pedestrian densities in building planning.

The advantage of integrating the knowledge of maps outside the building in the movement models was not visible since the walk outside was very short as can be seen in Figure 9. Longer walks outside the building in order to have a deeper view on the added value of integrating maps in the movement models to the overall positioning performance are foreseen for future publications.

Future work will also be in validating the model through observing the true human motion (recorded from many test subjects over longer time) and comparing it with what our model would propose in the same conditions. This approach will provide us with a measure of the probabilistic accuracy of our new model.

Implementation of other movement models such as the Social Force Model is also foreseen for future considerations. This will bring us a step further toward modeling all types of pedestrian’s movements and their motivations.

7. ACKNOWLEDGMENTS

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8. REFERENCES

- [AMGC02] S. Arulampalam, S. Maskell, N. Gordon and T. Clapp: A Tutorial on Particle Filters for On-line Non-linear/Non-Gaussian Bayesian Tracking, IEEE Transactions on Signal Processing, Vol. 50, No. 2, Feb. 2002
- [GSS93] N. Gordon, D. Salmond, and A. Smith, Novel approach to nonlinear and non-Gaussian Bayesian state estimation, vol. 140. Inst. Elect. Eng., 1993
- [KKRA09] M. Khider, S. Kaiser, P. Robertson, M. Angermann, A Three Dimensional Movement Model for Pedestrian Navigation, ENC-GNSS 2009, Naples, Italy, Mai 2009.
- [Hel92a] Dirk Helbing: Models for Pedestrian Behavior, Natural Structures. Principles, Strategies, and Models in Architecture and Nature, Part II (Sonderforschungsbereich 230, Stuttgart, 1992)
- [Tek02] Kardi Teknomo: Microscopic Pedestrian Flow Characteristics: Development of an Image Processing Data Collection and Simulation Model, PhD Dissertation, 2002.
- [OkM93] Shigeyuki Okazaki and Satoshi Matsushita: A Study of Simulation Model for Pedestrian Movement with Evacuation and Queuing, Proceedings of the International Conference on Engineering for crowd safety, 1993.
- [HSBP00] Serge P. Hoogendoorn, Phil Bovy, Gas-Kinematic Modeling and Simulation of Pedestrian Flows, Transportation Research Record No. 1710, Traffic Flow Theory and Highway Capacity, 2000.
- [Hel92b] Dirk Helbing: A Fluid Dynamic Model for the Movement of Pedestrians, Complex Systems 6, 391-415, 1992.
- [Add05] J. D. Addison: Flow on Links: Yesterday, Today and Tomorrow, IMA 2005.
- [Hel91] Dirk Helbing: A Mathematical Model for the Behavior of Pedestrians, Behavioral Science 36, 298-310, 1991
- [Res04] Wolfram Ressel: Modeling and Simulation of Mobility, 1st International Workshop on Intelligent Transportation (WIT 2004); Hamburg, Germany, 2004.
- [YFL⁺03] L. Yang, W. Fang, L. Li, R. Huang, and W. Fan: Cellular automata pedestrian movement model considering human behavior, CHINESE SCIENCE BULLETIN -ENGLISH EDITION-2003, VOL 48; PART 16, pages 1695-1699.
- [WLF03] Fang Weifeng, Yang Lizhong, W. Fan: Simulation of bi-direction pedestrian movement using a cellular automata model, Science Direct, Physica A 321 (2003) 633 – 640, 2003.
- [DJT01] J. Dijkstra, A.J. Jessurun and H.J.P. Timmermans: A Multi-Agent Cellular Automata Model of Pedestrian Movement, Pedestrian and Evacuation Dynamics. Berlin, D: Springer-Verlag. 173-181, 2001.
- [HeM95] Dirk Helbing, Peter Molnar: Social Force Model for Pedestrian Dynamics, Physical Review E 51, 4282-4286, 1995.
- [LKF05] Taras I. Lakoba, D. J. Kaup, Neal M. Finkelstein: Modifications of the Helbing-Molnár-Farkas-Vicsek Social Force Model for Pedestrian Evolution, SIMULATION, Vol. 81, No. 5, 339-352, 2005.
- [MaS98] J. MacGregor Smith: Evacuation Networks, Encyclopedia of Optimization, 1998.
- [OsB07] Carolina Osorio and Michel Bierlaire: An analytic finite capacity queuing network capturing congestion and spillbacks, TRISTAN VI, EPFL, 2007.
- [BPWR05] On Map-Matching Vehicle Tracking Data, Sotiris Brakatsoulas, Dieter Pfoser, Carola Wenk, Randall Salas, VLDB, 2005
- [Sco94] Craig Scott, Improved GPS Positioning for Motor Vehicles through Map Matching, Proceeding of Ion GPS-94, Salt Lake City
- [KSR07] Map matching, M. Khider, F. Schubert, P. Robertson, Technical Note for GalileoADAP project, German Aerospace Center (DLR), 2007
- [KKRA08] M. Khider, S. Kaiser, P. Robertson, M. Angermann, A Novel Movement Model for Pedestrians Suitable for Personal Navigation, ION NTM 2008, San Diego, California, Jan. 2008
- [TTC04] Nerius Tradišauskas, Dalia Tiešytėdalia, Christian S. Jensen, A Study of Map Matching for GPS Positioned Mobile Objects, 7thWIM Meeting, Uppsala, Sweden, September 2004.
- [PeL99] Pentland and A. Liu, Modeling and Prediction of Human Behavior, Neural Computation, vol. 11, no. 1, pp. 229–242, 1999.
- [ZhN02] T. Zhao and R. Nevatia, 3D Tracking of Human Locomotion: A Tracking as Recognition Approach, in 16th International Conference on Pattern Recognition, 2002, December 2002.

[AdA04] A. Adam and S. Amershi, Identifying Humans by Their Walk and Generating New Motions Using Hidden Markov Models, The University of British Columbia, Topics in AI: Graphical Models and Computer Animation, Tech. Rep., December 2004.

[WKAR06] Wendlandt, Khider, Angermann, Robertson: Continuous location and direction estimation with multiple sensors using particle filtering, IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems, 2006.

[Khi05] M. Khider, Implementation of a Simulator/Demonstrator for the SoftLocation Concept using Bayesian Filters, Master Thesis, University of Ulm, 2005

[ScA93] G. K. Schmidt and K. Azam, Mobile robot path planning and execution based on a diffusion equation strategy, in Advanced Robotics, Vol. 7, No. 5, pp. 479-490, 1993.

[KAL03] J. Kammann, M. Angermann and B. Lami, A new mobility model based on Maps, in VTC 2003.

[KrR08] B. Krach, P. Robertson, Integration of Foot-Mounted Inertial Sensors into a Bayesian Location Estimation Framework, Proc. 5th Workshop on Positioning, Navigation and Communication 2008, (WPNC 2008), Hannover, Germany, Mar. 2008.

[ROAW02] P. Robertson, A. Ouhmich, M. Angermann, and K. Wendlandt, Implementation of soft location on mobile devices, in International Symposium on Indoor Localization and Position Finding, InLoc 2002, DGON, Bonn/Germany, July 2002.