

The Effect of Maps-Enhanced Novel Movement Models on Pedestrian Navigation Performance

Mohammed Khider, Susanna Kaiser, Patrick Robertson, Michael Angermann, *German Aerospace Center (DLR), Germany*

BIOGRAPHY

All authors are with German Aerospace Center, Institute of Communication and Navigation, 82234 Wessling, Germany, <name>.<lastname>@dlr.de, correspondence Author: Mohammed Khider, Phone ++49 8153 28 2830.

ABSTRACT

In this paper the question of “how much the a priori knowledge of floor plans will assist navigation in challenging indoor environments?” will be investigated. Additionally, the effect of different levels of accuracy of floor plans on the overall estimation process will be studied. In particular, the effect of wrong a priori knowledge of maps and floor plans on navigation accuracy will also be illustrated.

The knowledge of floor plans is used to make the prediction step of *sequential Bayesian estimation* [AMGC02] more realistic. A combination of two movement models assisted with the knowledge of floor plans, operating at the microscopic level and suitable for pedestrian navigation are developed to be used in the prediction step. The constituents are a Map-Enhanced Stochastic Behavioral Movement Model to characterize more random motion and a Diffusion Movement Model to characterize a geographic goal a pedestrian might walk towards. A top-level Markov process is used to determine whether to currently use the stochastic behavioral or the diffusion model; therefore, the model switches between motion that is more goal oriented (diffusion model) or stochastic. Both models use the a priori knowledge of floor plans differently.

The technique through which the knowledge of floor plans is included in each of the two movement models will be explained. Additionally, the effect of the knowledge of various densities of walls on the overall estimation process will be analyzed.

1. INTRODUCTION

It is widely known that most positioning applications benefit when map information aids the positioning sensors. A common example is map matching in automotive navigation systems [Sco94] where the fact that the vehicle is located on a known road layout is used

to reduce the positioning uncertainty, and to make routing possible at all. For pedestrian navigation the situation is usually not so simple: a person may choose to move across a much more diverse area than just a set of roads. However, even in these cases and especially for indoor positioning a pedestrian can still walk only in certain areas, as restricted by the layout of a building, for instance. In this paper we will quantitatively explore the value of such a building layout for pedestrian navigation. It is important to note that we shall do this in the context of *dynamic* positioning, in other words we will not simply perform some sort of map-snapping, or restriction of the position to a valid building portion. Rather, we will model the dynamic nature of the motion of the user in conjunction with the building plan within a probabilistic estimation framework. The building layout will effectively restrict the range of movement a pedestrian can make and we wish to quantify the benefits this will have on overall positioning accuracy.

1.1. INTEGRATING MAPS AND FLOOR PLANS INTO NAVIGATION ALGORITHMS

Dynamic indoor positioning and urban canyon navigation are application areas that are becoming increasingly important. Efficiency, reliability and accuracy of these applications can be improved if the knowledge of maps and floor plans is used. This can be done via the use of Maps-Enhanced Pedestrian Movement Models. The reason that a movement model is needed in these cases lies in the dynamic nature of most pedestrian indoor navigation applications: The user's position will be estimated continuously so as to allow services such as personalized travel assistance or indoor navigation directions. In addition, it can be shown that 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. Enhancing the used movement model with the a priori knowledge of maps and floor plans brings it closer towards reality and accordingly make the pedestrian navigation more accurate. With such knowledge, the pedestrian 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 and not entering restricted areas and who is

attracted toward points of interest. This is in addition to many other possible movement constraints which improve the model.

To implement mathematically sound dynamic estimators one needs an accurate and realistic map-enhanced movement model (also known as the a priori state transition model) of the dynamic system: Here the user's stochastic movement (position, velocity, attitude, etc.) is represented. Within the scope of this paper, the purpose of such movement models is to simulate a single pedestrian's movement as realistically as possible, so that it can be applied to positioning.

In the context of previous dynamic estimators we have grounded our work on the formalism of sequential Bayesian estimation, 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, and in order to do so correctly it needs to incorporate the possible changes of the system's state from one time instance to the next. Essentially, the more "predictable" the system state transitions are, the more the measurements can be filtered over time. If measurements happen to be unavailable for one or more time steps, then the movement model yields a prediction of the state estimate. Dead-reckoning essentially builds on this principle whereby the underlying movement model is a very simple one. Better and map-enhanced movement models will of course improve the accuracy of the sequential Bayesian estimator.

The map-enhanced movement model presented here is used in the prediction step of a dynamic location and direction sequential estimator that uses particle filtering as the fusion engine. It is also 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. PREREQUISITES FOR A NAVIGATION MOVEMENT MODEL

In sequential Bayesian estimation the choice of algorithm will affect the way in which the movement model is incorporated. For estimation of non-linear and non-Gaussian processes, and especially in situations where the state estimates are multimodal, one often resorts to sequential Monte Carlo (SMC) techniques, such as Particle Filtering [AMGC02] [GSS93]. In this case and specifically for pedestrian navigation applications, we propose that the movement model must fulfill the following conditions:

1. It must be statistically accurate in describing the state transition probabilities $\text{Prob}\{x_k | x_{k-1}\}$; this represents the probability of all possible system

states at time k , given a certain known system state at $k-1$. In our case, the model describes the probability distribution of the user's position, velocity, attitude, as well as other parameters, given the knowledge of these parameters one time-step previously.

2. For particle filtering applications with transition probabilities as the importance function one must be able to efficiently draw samples from, and compute, the state transition probabilities $\text{Prob}\{x_k | x_{k-1}\}$ for any given previous state x_{k-1} .
3. The model should take into account individual variances of the user, such as their walking speed.
4. It must take into account the known building layout, such as walls, doors, stairs, as well as other local factors affecting pedestrians' motion.
5. Ideally, motion in both 2D and 3D motion should be represented.
6. It must incorporate at least position, speed and heading.

An example of a very simple movement model that does not fulfill all requirements above is that where the heading and speed follow a (bounded) random walk process [PSAE96] with additive white Gaussian process noise. This model cannot incorporate walls or the fact that people generally walk along corridors.

1.3. SUMMARY OF RELATED WORK

1.3.1. MOVEMENT MODELS

Some movement models provide only statistical measures like means and densities; on the other hand others provide a detailed model of pedestrian behavior. Detailed behavioral models are the required ones for navigation – the main application of this paper.

Some special movement behaviors have to be considered for some specific applications. For example a movement model that will be used to model firemen or rescuers has to consider some special behaviors like sliding, climbing, jumping and rolling.

Models for pedestrian movement are developed at three different levels. They are the mesoscopic, the macroscopic level and the microscopic level [Hel92a] [Tek02].

Mezoscopic modeling was primarily designed for traffic simulations, but later applied to pedestrian modeling. Here, the pedestrian behavior is described via approximate equations for the mean values of velocities as a function of some parameters like the pedestrian's age or activity.

At the *macroscopic level* 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 sufficient to model the human behavior.

At the *microscopic level* every pedestrian is treated as an individual and the behavior of pedestrians' interaction is observed. A microscopic description is more of interest in the navigation domain. They also have practical applications in designing evacuation plans and pedestrian areas, and as an experimentation & optimization design tool. Accordingly, the work in this paper addresses the microscopic modeling approach.

There exist several analytical models that try to describe the microscopic behavior of a pedestrian. They are based on granular-physics of flow. The mathematical formulation of microscopic models generally leads to complicated equations that are impossible to be solved analytically and hard to be solved with a computer [Tek02]. But they can be approached using Monte Carlo Simulations. These kinds of simulations are called Microscopic Pedestrian Simulation Models (MPSMs). MPSM is a computer simulation model of pedestrian movement where every pedestrian in the model is treated as individual.

All levels of description of pedestrian movement models take into account pedestrian *intentions* and *interactions*. At the Microscopic level, the pedestrian is affected by two forces. The first pushes the pedestrian toward his goal and the other introduces a repulsive force to push the pedestrian far from other pedestrians and obstacles. Geographical, spatial and geometrical environments are essential parameters that have to be considered in a reasonable pedestrian model.

In the literature, there are several microscopic pedestrian simulation models that include the Social Force Model [HeM95] [LKF05], Magnetic Force Model [OkM93], Benefit Cost Model [Res04] [Tek02], Cellular Automata Model [YFL+03] [WLF03] [DJT01], and Queuing Network Model [MaS98] [OsB07].

In this paper, a combined behavioral - diffusion movement model [KKRA08] designed especially for indoor navigation environments and makes use of the a priori knowledge of maps and floor plans is used. This model fits more indoor navigation applications compared to the random walk [KKRA08].

1.3.2. 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. An illustration of Classical Map Matching is shown in Figure 1.

The basic four steps of Classical Map Matching are [TTC04]:

1. Extract information from the available position sensor.
2. Select candidate polylines (curves) set from the whole polylines group. The selected polylines are those lying within a specific distance threshold from the position measurement.
3. Apply some specific algorithm to select a polyline from the above set.
4. Estimate the position of the tracked object inside that polyline.

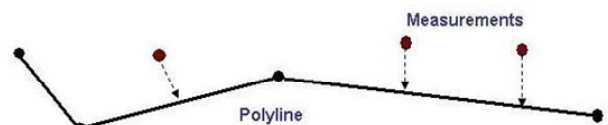


Figure 1: Classical Map Matching. Measurements are snapped to the nearest points in the nearest path.

Some weighting approach might be used to give some importance to some parameters compared to others. Combining these parameters in a sensible manner will obviously help selecting the right polyline. Variable weights are assigned to the affecting parameters according to the tracking object and the situation itself.

In *Movement Models Based Map Matching* [KSR07], the map is used to restrict the otherwise 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 according to the tracked object in Movement Model Based Map Matching. 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.

Figure 2 shows the development of the probability densities using the two methods in the same corridor. With the a priori knowledge of the walls in the Movement Model Based Map Matching, the probability density gets more concentrated since it will be trimmed at

the walls. It is clear from the example that Movement Model Based Map Matching can provide better accuracy compared to Classical Map Matching when used in a sequential estimation process.

In this paper, we use a floor plan to restrict the movement of pedestrian, so that crossing walls is not allowed. In combination with the diffusion movement model, the movement model based map matching is applied in the sense that the floor plan is used to restrict the possible areas where movement is more reliable.

2. A MAP-ENHANCED COMBINED DIFFUSION AND STOCHASTIC BEHAVIORAL MODEL

A. A MAP-ENHANCED STOCHASTIC BEHAVIORAL MOVEMENT MODEL

Human movement at the kinematical level is parameterized by physical parameters such as speed, direction of motion and position. However, speed and direction are affected by several “human” states. Examples of these states are pursued activity, emotions, degree of disorientation, age, obstacles and weather. Some of these parameters affect the movement more than others. Building layouts are obviously amongst the main parameters that affect the movement of the pedestrian. For instance, the pedestrian cannot penetrate a wall under any normal circumstances.

Eleven parameters that affect the human movement are considered during this work. These parameters are categorized into two groups, where the first category includes parameters that the system can determine accurately and the other category includes parameters

that are varying according to the human behavior. They can be extended or modified according to the scenario and the application. The system is used to specify the new states of the first category parameters such as time of day, weekday, age, obstacles, ground steepness and weather. Markov chains are used to specify the new states of the second category parameters such as emotions, disorientation, activity, activeness and arousal. The idea of using Markov Chains for describing human behaviors could also be found in [PeL99], [ZhN02] and [Ada04]. Some of the first category parameters such as weather, obstacles and steepness depend on the pedestrian’s current position.

Our *stochastic behavioral movement model* assumes that given the specific instantiation of our eleven parameters, the physical motion parameters of the pedestrian can be specified with reasonable accuracy. Given the user’s current situation with respect to these eleven parameters, the next step which our model follows is to stochastically draw the pedestrian’s actual movement following a distribution function that is conditioned on these eleven parameters. To do so, a Gaussian distribution was assumed for the main physical random variables; speed and the direction. The values of the mean and the standard deviation of the user’s speed and direction, given the specific values of each of the eleven parameters variables are predetermined. They are based on statistical data [Bek95] [GrG04] as well as common-sense assumptions.

Each of our eleven parameter results in a specific mean and standard deviation of the pedestrian’s speed and direction. A weighted average is used to combine these means and standard deviations into a single mean

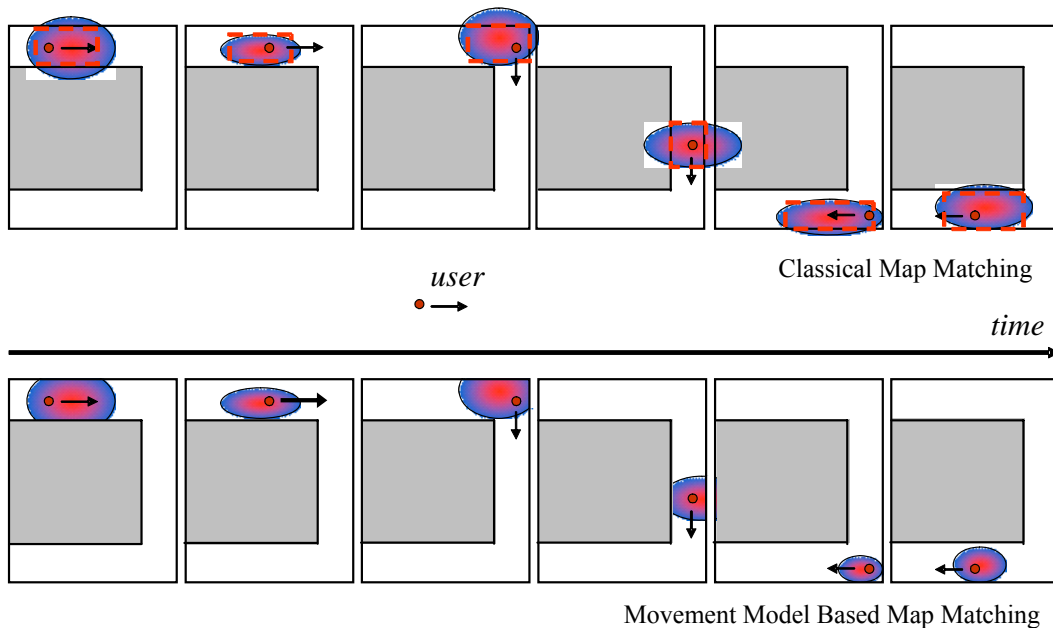


Figure 2: Comparison between Classical Map Matching and Movement Model Based Map Matching; latter procedure exhibits clearly smaller blur after second bending, while Classical Map Matching obtains profit from the use of the walls only at short notice

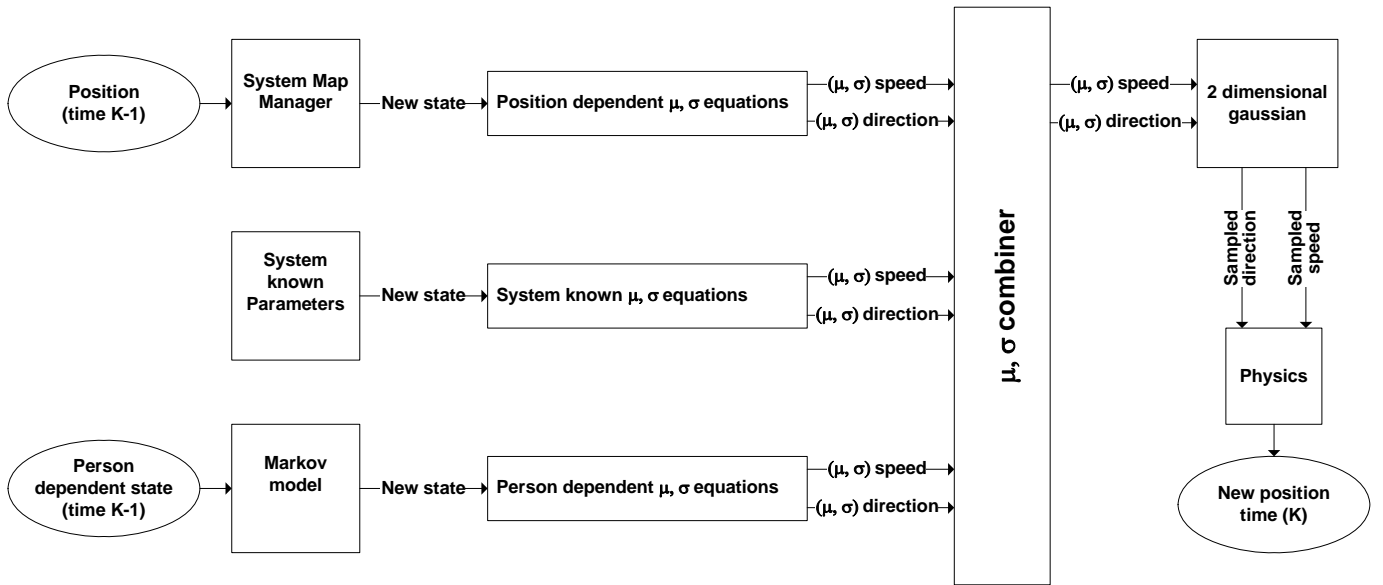


Figure 3: Stochastic Behavioral Movement Model

and standard deviation for speed and direction. The combination results are then used to parameterize our Gaussian distributions. New speed and new direction values are then drawn from these Gaussian distributions.

Finally, the position at the next time step is calculated as a function of the drawn speed and direction using the equations of motion and the old position. In this way, we have drawn a new value of the state x_k from $\text{Prob}\{x_k | x_{k-1}\}$ given the old state. The state x_k comprises all above mentioned eleven parameters that are drawn according to their Markov process or known a priori (e.g. age, weather), as well as the physical motion states (heading, speed, position).

The states of our eleven parameters evolve over time resulting in variations in the pedestrian's speed and direction and accordingly in his position. A flow diagram of how the Stochastic Behavioral movement model works is shown in Figure 3. Details of this model can be found in [WKAR06] and [Khi05].

Whereas this model is 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. As we demonstrated in [KKRA08], this model leads to a high probability of becoming "stuck" in a room. This is because the random movement which the model is following does not react to the presence of a door.

To incorporate the a priori knowledge of floor plans in the stochastic behavioral model a modified wall bouncing approach is followed. The algorithm checks at every time step if the suggested movement will result in crossing any of the walls. If a wall cross results, then a movement that is parallel to the crossed wall in the same general direction of movement will be followed. If after several tries, other neighboring walls are still crossed,

then a movement that is perpendicular to the crossed wall will be followed.

B. DIFFUSION MOVEMENT MODEL

To overcome the problem of staying in a room for a longer time with the above described model and for the simulated pedestrian not being able to find a suitable exit, the *diffusion movement model* taken from [KAL03] is applied. This model is derived from the principle of gas diffusion in space studied in thermodynamics and is originally a standard solution for path finding of robots [ScA93]: The idea is to have a source continuously effusing gas that disperses in free space and which gets absorbed by walls and other obstacles. The path from any point towards the source is then computed by following the gradient of the concentration until reaching the source. To keep the model's complexity low, the diffusion movement model is confined to a rectangular area. The central assumption of our model is that a pedestrian will walk along a "sensible" path from her current location to some destination randomly changing the destination she is walking towards.

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

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

a so called diffusion matrix \mathbf{D}_m is pre-computed. 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/source point (Figure 4, red points are

destination points, gas concentration is high in the dark red area and low in the blue area).

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.

We prefer to use the more realistic path and keep the computation effort during running the movement model low by pre-computing the diffusion matrix \mathbf{D}_m for all destination points and storing the angle of the direction of the path in an angle matrix \mathbf{A}_m . The angle matrix \mathbf{A}_m contains for each position in the rectangular area the value of the angle of the direction towards destination point W_m .

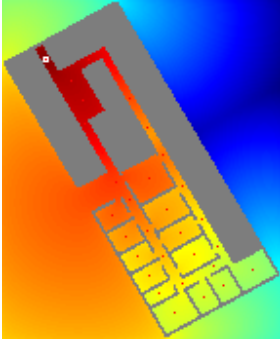


Figure 4: Diffusion Matrix for gas effusion from one destination point (white circle)

To make the model probabilistic, the destination points are chosen randomly (assuming here a uniform distribution). The destination is changed with some assumed probability to take into account the individual variances of the user, such as changing her destination. The speed of the pedestrian is predicted with the stochastic behavioral movement model. A more detailed description of the whole algorithm can be found in [KKRA08].

With the diffusion movement model the modeled pedestrian “finds” the exit of a room faster than with the stochastic behavioral movement model, especially when the door opening is small, given that with a high probability there will be a source of gas outside the room. The disadvantage of using the diffusion movement model is that the true destination point is not known and may not be in or close to our set of N_w destinations. Furthermore, 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. Therefore, a combination of both models is particularly advantageous [KKRA08] and will be applied in our simulations.

The floor plan is used via the layout map matrix within the diffusion movement model. The layout map matrix \mathbf{L} defines the accessible and inaccessible areas for pedestrians with

$$l_{i,j} = \begin{cases} 1 & \text{if } l_{i,j} \text{ is accessible} \\ 0 & \text{if } l_{i,j} \text{ is not accessible} \end{cases} \quad \forall i, j: i=0, \dots, N_x, j=0, \dots, N_y \quad (3)$$

where $N_x \times N_y$ is the size of the rectangular area. To compute the Diffusion Matrix \mathbf{D}_m the matrix is element-wise multiplied with the layout map matrix \mathbf{L} , therefore, the values of the diffusion matrix are set to zero at the walls.

Because of the walls, no gas goes through the walls. Therefore, a person will never go through the walls. In addition, the values near a wall will never have a higher value than in the middle of the room. Therefore, the path will not hit a wall.

C. A MAP-ENHANCED COMBINED MOVEMENT MODEL

The behavioral and the diffusion movement model are combined via an extended Markov model (see Figure 5). The combined model switches between motion that is more stochastic (Section 2.A) or goal oriented (Section 2.B).

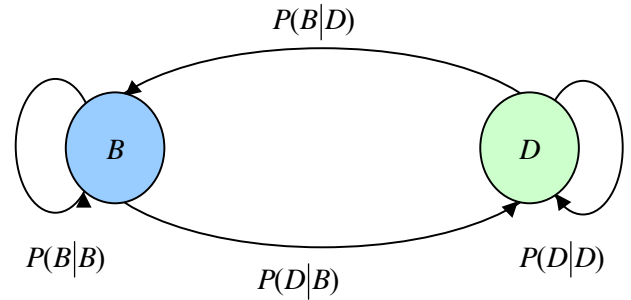


Figure 5: Markov Model

The Markov model contains two states: state B where the behavioral movement model is used and state D where the diffusion movement model is used. In addition, we have the transition probabilities $P(D|B)$ and $P(B|D)$, and the same-state probabilities $P(B|B)$ and $P(D|D)$.

In our case, the same-state probabilities are large and the transition probabilities are very small. Therefore, if the behavioral movement model is used, it will be applied several times and changing the movement model happens only occasionally. With this, the combined model switches between both models randomly with a small transition probability, where each model may be successively used for several time steps.

3. POSSIBLE DISCREPANCIES BETWEEN ASSUMPTION AND REALITY

In our Map-Enhanced Stochastic Behavioral Movement Model we make use of knowledge about building layouts, i.e. the geometry of walls, doors, passages and the like that define the accessible areas for a tracked person. The benefits of this approach are twofold:

Firstly, the probability distributions resulting from the random process have less distance to the “real” process. In unreachable places the distributions correctly have no support (“zero probability”). Furthermore, the dynamics of the process is involved: intricately tying the user motion to possible trajectories within the building. Consequently, this leads to more accurate estimation of the position probability density function or less average error, i.e. improved accuracy for derived point estimates. Secondly, when applying Monte-Carlo-based Sequential Bayesian Filtering (“Particle Filtering”), we can reduce the number of necessary particles by not investing particles on unreachable places. This reduces computational complexity, or, if the number of particles is kept constant, will also result in increased accuracy. Ideally, we would have complete and exact knowledge about building layouts. In reality our knowledge will neither be complete, nor exact. Our experimental campaigns have shown that it is important to take this fact into account in order to derive viable pedestrian navigation systems.

Figs. 6 and 7 show the four cases of a simplified model with two correct (Cases I and III) and two false assumptions (Cases II and IV) to represent the incomplete knowledge about layout. This model is well-suited to study the result of changes to the building structure such as newly erected walls or uncharted doors.

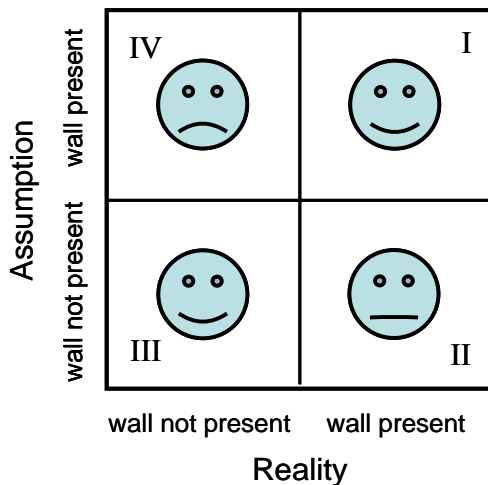


Figure 6: Discrepancies between reality and assumption. Whereas neglecting a wall that exists in reality (Case II) may lead to slightly suboptimal accuracy and efficiency, wrongly assuming a wall where in reality there is none (Case IV) may lead to complete loss of tracking or significant errors. Cases I and III represent correct assumptions.

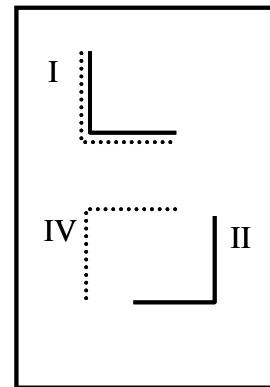


Figure 7: Illustration of the four cases. Solid lines depict real walls, dotted lines depict assumed walls. Assumption and reality match in Case I. In Case II a real wall is present that is not represented in the assumption. In Case IV a wall is falsely assumed that does not exist in reality. All other regions are representatives of Case III.

A tracked person will avoid all walls (see Fig. 8). If the wall is unknown to the movement model (e.g. a newly built wall that has not been added to the CAD model) particles will not avoid the wall. Hence, some particles will represent impossible hypotheses and are “wasted”. However, this effect is not severe, since usually sufficient particles will be able to follow the true path.

It is interesting to become aware that all navigation schemes that do not use map information implicitly make all errors associated with Case II.

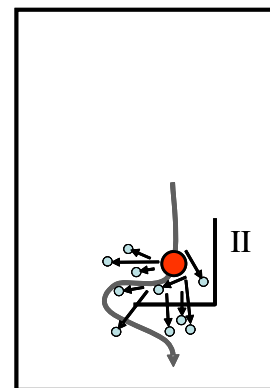


Figure 8: Presence of an unknown wall (Case II). The true movement of the person (large red dot) results in avoiding the wall. Since the movement model does not assume the wall, particle movement does not avoid the wall and some are “wasted”. However, a sufficient number of particles follow the person. This case is identical to the situation of systems that do not take map information into account.

Changes in a buildings structure may also lead to Case IV, i.e. assuming the presence of walls where there

is none (see Fig. 9). A person will then proceed in her or his path undisturbed, whereas the assigned movement model will not allow particles to pass the assumed wall. This may lead to particles becoming “stuck” at the non-existent wall. The stuck particles will correctly be given lower and lower weight due to their increasing mismatch with measurements in subsequent steps. In consequence, this may lead to severe depletion of particles and eventually loss of tracking.

An extreme measure to avoid this effect would be the complete ignorance of any map knowledge and return to “old” movement models that always act as if no walls were present. Clearly, the resulting loss in accuracy and computational efficiency that is evident from the simulations (see later) is unwanted. Ideally, the probability with which an assumed wall does not exist should be properly represented. However, since the scope of this paper is the principle evaluation of the effects of map models, we refrain from discussing solutions and postpone this to further work.

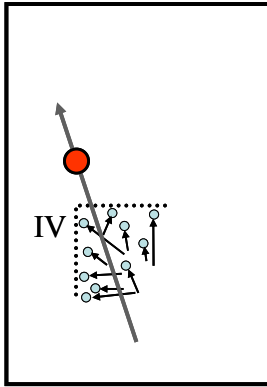


Figure 9: Falsely assumed wall (Case IV). The true movement of the person (large red dot) passes right through the falsely assumed wall. The movement model will not allow particles to pass through. A significant number of particles may get stuck, and eventually tracking fails.

4. SIMULATION ENVIRONMENT AND EXPERIMENTAL SETUP

Sequential Bayesian Estimators are widely used in estimation problems that are related to noisy sensors. They provide two main benefits: First, sensor outputs are represented using probability distributions instead of hard decisions which helps in combining several heterogeneous sensors. Second, it allows including the system dynamics (the movement models) in the estimation process. Through the use of movement models, floor plans and maps could be incorporated and as a result, a more accurate estimation process could be achieved.

Qualitative and quantitative analysis of the effect of floor plans on the overall estimation process were

required. The effect of floor plans was tested in an already available distributed simulation and demonstration indoor/outdoor environment for positioning. The environment allows plugging-in several types of sensors, Bayesian Filters and movement models. Testing the implemented movement model using the above environment can help us in obtaining a quantitative measure on the effect of the accuracy of floor plans on the navigation accuracy. It also gives quantitative measures on how much inaccurate floor plans may worsen the overall estimation process.

Additionally, a quantitative comparison between an accurate floor plan that is dense with walls versus another accurate floor plan that has a lower density of walls is made.

The environment mentioned above was used in the simulation mode to obtain the required analysis. The measurements were drawn from the simulated positions and directions of the pedestrian based on sensor measurement models: Gaussian noise is added to the simulated positions and directions to obtain the simulated measurements. The map-enhanced movement model is used to move the simulated pedestrian and the particles from one time step to the next. The Sequential Bayesian Estimator uses only the noisy measurement and tries to estimate the pedestrian position. The error between the estimated position and the real pedestrian position was recorded.

The first quantitative measure was made by passing the complete amount of walls in the floor plan to the movement model used by the simulated pedestrian while passing smaller sets of walls to the movement model used by the estimator. The accuracy of the estimated position was measured as a function of the density of walls passed to the estimator.

A qualitative measure was obtained by comparing the estimation accuracy when using a denser floor plan and a less dense floor plan. This was done by passing different numbers of walls to the simulated pedestrian and monitoring the estimator performance. Again, the accuracy of the estimated position using each amount of walls was observed as a function of the density of walls passed to the estimator. The generated curves were compared and analyzed.

A third quantitative measure was made, assuming walls that are not passed to the simulated pedestrian and passing them to the estimator. That was done to test the effect of incorrect floor plans on the overall estimation process.

5. SIMULATION RESULTS

From Figure 10 and 11, it is clear that the knowledge of floor plans leads to improvements in the position estimation accuracy, and in turn, the overall indoor navigation performance. Additionally, we can see that as the knowledge available to the estimator about the floor plan increases, the average linear error decreases. This

result in fact proves that a map-enhanced movement model is a key factor in solving the challenge of indoor and urban canyons navigation.

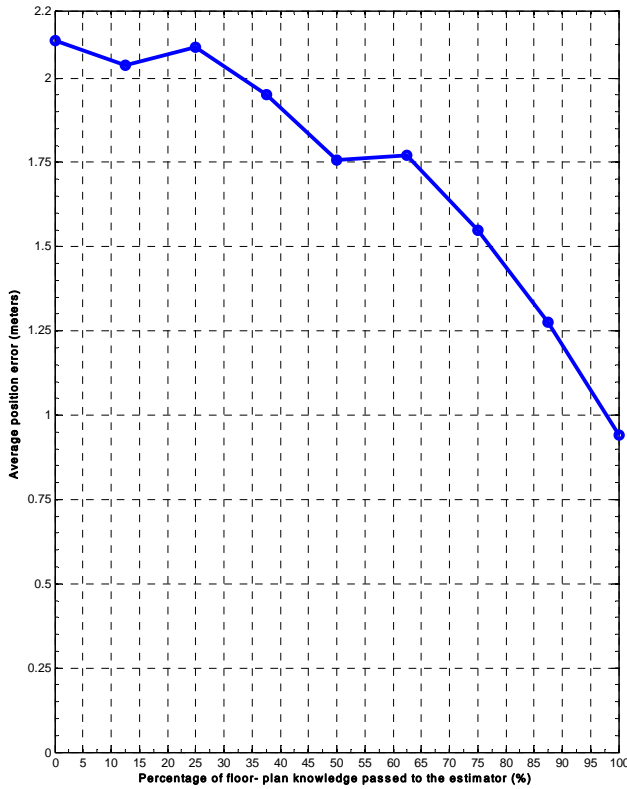


Figure 10: Average position Error vs. Percentage of floor-plan knowledge with a floor that has a total of 40 walls

Unexpectedly, we can see from Figure 10 that the estimator knowledge of 25% of the floor plan resulted in a higher error compared to the estimator knowledge of 12.5%. That was because the random extra 12.5% walls added in the 25% case resulted in walls touching each other and constructing some corners (traps) for the particles. As a result, the particle cloud sometimes becomes stuck in these traps and results in degrading the overall accuracy. The same observation is valid when comparing the 62.5% knowledge with the 50%. The effect becomes particularly apparent when using small numbers of particles. As the number of particles increases, this effect occurs less often. In order to reduce the effect of this phenomenon, we distributed the corners manually more evenly over the different percentages of floor-plan knowledge.

Comparing Figure 10 and 11, we can see that a less dense simulated floor plan shows a better performance compared to the dense one. To explain this behavior let

us take the point where zero walls are passed to the estimator in the denser floor plan (Figure 10) and the less dense floor plan (Figure 11). Actually, even if no walls are passed to the estimator in the less dense floor plan, the difference between the simulated pedestrian and the estimator is less than in the case of the denser floor plan. Accordingly, the movement model used by the estimator will be closer to the one used by the simulated pedestrian in the case of the less dense floor plan. This will result in a more accurate estimation in the less dense floor plan scenario compared to the denser floor plan scenario. On the other hand, both the simulated pedestrian and the particles will move more realistically and closer to the normal human behavior in buildings in the denser floor plan compared to the less dense one.

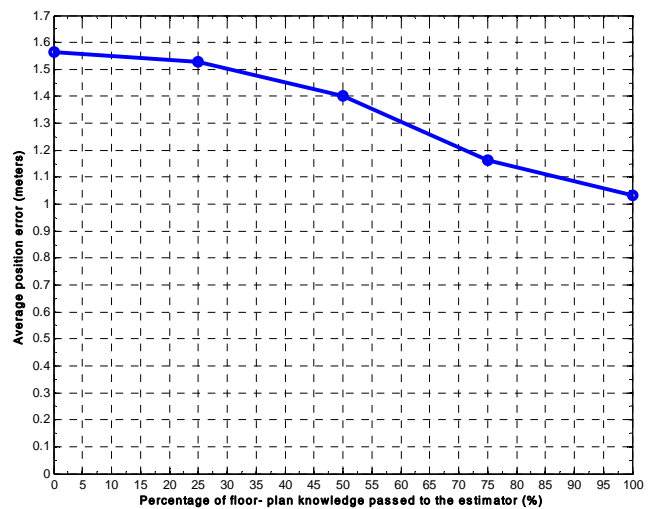


Figure 11: Average position Error vs. Percentage of floor-plan knowledge with a floor that has a total of 20 walls

From Figure 12, it is obvious that as more wrongly assumed walls are passed to the estimator, the worse the overall estimation accuracy becomes. It can also be noticed that the deterioration in the overall navigation performance that results from passing non-present walls is bigger than that resulting from the lack of the knowledge of some walls.

As can be observed from Figure 12, the estimator has shown a better performance in the case of 20 wrong walls passed to it compared to the 15 walls case. The explanation of this unexpected result is that the extra walls added in the 20 walls case resulted in reducing the corners (particles traps) by generating some closed areas that are generally unavailable to both particles and the simulated pedestrian.

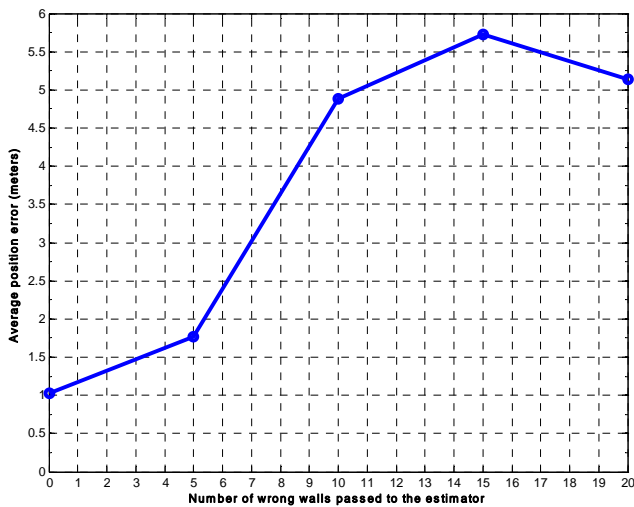


Figure 12: Average position error vs. Number of wrong walls passed to the estimator with a floor that has a total of 20 walls

6. CONCLUSIONS AND OUTLOOK

In this paper we have quantitatively analyzed the effect that knowledge of a building plan will have on a typical indoor positioning scenario for pedestrian navigation. By varying the density of walls we have seen that there is a direct improvement of positioning accuracy with an increasing number of known walls in the building plan. For our scenario, the error was reduced by a factor of two in terms of average error. Our work has exposed a potential problem with wall-assisted estimation in conjunction with particle filtering: the number of particles needs to be typically higher as the density of walls increases, so as to avoid particles losing track of the real position for some while if they are once separated from the true position by walls. The problem appears very clearly if the added walls resulted in some corners that trap the particles in some directions. The result will be a pedestrian walking in some direction and particles that are unable to follow him since they are trapped. We have also looked at the effect of erroneous walls in a building layout, i.e. walls that are assumed to be present but which are not in actual fact. These “walls” have the detrimental effect of overly limiting the modeled motion of the pedestrian and result in severe degradation of accuracy.

Further work will address overcoming the above mentioned problems by employing strategies to model uncertainty of walls’ existence or precise location for example by making walls penetrable by particles. Even if the wall layout is known to be accurate, such an approach might also allow the number of particles to be reduced. Other work should also look at how different sensors are aided by a layout and for which sensor combinations a known layout is particularly beneficial. This will take us

one step closer to the vision of location and situation based services.

7. ACKNOWLEDGMENTS

Special thanks to all the Broadband System Group members for their encouragement and support.

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
- [Sco94], Craig Scott, “Improved GPS Positioning for Motor Vehicles through Map Matching”, Proceeding of Ion GPS-94, Salt Lake City
- [GSS93] N. Gordon, D. Salmond, and A. Smith, “Novel approach to nonlinear and non-Gaussian Bayesian state estimation,” vol. 140. Inst. Elect. Eng., 1993
- [PSAE96] Bradford W. Parkinson, James J. Spilker Jr., Penina Axelrad and Per Enge, Global Positioning System: Theory and Applications, Vol. 1, chapter 9, 418-420, Institute of Aeronautics and Astronautics, Inc., Washington, D.C., 1996
- [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.
- [Hel92b] Dirk Helbing: A Fluid Dynamic Model for the Movement of Pedestrians, Complex Systems 6, 391-415, 1992.
- [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.
- [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.

[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.

[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.

[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.

[BPWR05] On Map-Matching Vehicle Tracking Data, Sotiris Brakatsoulas, Dieter Pfoser, Carola Wenk, Randall Salas, VLDB, 2005

[KSR07] Map matching, M. Khider, F. Schubert, P. Robertson, Technical Note for GalileoADAP project, German Aerospace Center (DLR), 2007

[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, 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.

[Bek95] G. A. Bekey, "Walking," The Handbook of Brain Theory and Neural Networks, MIT press, pp. 1045-1049, 1995.

[GrG04] R.D. Green, and L. Guan, "Quantifying and Recognizing Human Movement Patterns from Monocular Video Images - part I: A new Framework for Modeling Human Motion," IEEE Transactions on Circuits and Systems for Video Technology, pp. 179-190, 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

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

[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.