A THREE DIMENSIONAL MOVEMENT MODEL FOR PEDESTRIAN NAVIGATION

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BIOGRAPHY

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ABSTRACT

Pedestrian mobility models can be used for numerous applications such as 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 three dimensional pedestrian's movement. Our own application focus is to generate a "movement" or transition model for sequential Bayesian filtering techniques, such as particle-filtering [AMGC02] [GSS93], but the method can be applied to many of the above application domains.

In this paper the two dimensional movement model presented in [KKRA08] is extended in order to be able to accommodate pedestrian movement in the rectangular coordinate system of X, Y and Z. Here, X and Y represent the earth surface plane in a local region, and Z is the upward normal vector to that plane. The result is a three dimensional mobility model that is capable of representing pedestrian movement in challenging indoor and outdoor localization environments such as multi-floor buildings. It actually consists of two constituent 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 more goal-directed motion and more random motion, a top-level Markov process is designed to determine whether to currently use the 3D-SBMM or the 3D-DMM. Therefore, the model switches between motion that is more goal-oriented (3D-DMM) or stochastic.

The designed model is implemented and tested in an already available distributed simulation and demonstration indoor/outdoor environment for mobility, location and context applications.

Applications of pedestrians' movement models, as well as pre-requisites for a localization movement model and 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. System design and implementation will be illustrated in section 3. Simulation results will be given in section 4. Finally, some conclusions and future work will be given in section 5.

1. INTRODUCTION

1.1. APPLICATIONS OF MOVEMENT MODELS

Pedestrian movement in the field of dynamic indoor positioning is investigated in this paper to represent the stochastic nature of pedestrian movement [Hel92a] [Tek02] [OkM93]. 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. On the other hand, dynamic positioning systems are 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. Assumed here is the formalism of sequential Bayesian estimation, of which the well known Kalman Filter is a special case [AMGC02].

The sequential Bayesian Estimator draws an estimate of a system's state over the course of time from a probability distribution, and then updates the estimate by incorporating the new observations as they become available. 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 often allows a reasonable drawing of the state estimate. As an example of a very simple motion model, most portable automotive satellite navigation units extrapolate the vehicle's trajectory when entering a tunnel without reception.

1.2. SUMMARY OF RELATED WORK

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 as 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 mezoscopic models, macroscopic models and microscopic models [Hel92a] [Tek02].

Describing 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 is sometimes sufficient in the pedestrian behavior at the **mezoscopic** level [HSBP00]. Mezoscopic modeling was primarily made for traffic simulations, but later applied to pedestrian modeling.

It is sometimes the case that in addition 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 – this is denoted as **macroscopic** pedestrian modeling. The origins of these models are still the gas-kinetic equations and they also originate 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 Pedestrian Simulation Models (MPSMs). MPSM is a computer simulation model of pedestrian movement where every pedestrian in the model is treated as an individual. "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].

A microscopic description is more of interest in the navigation domain. They also have practical applications in the evacuations plans, the design of pedestrian areas, and as experimental & optimization design tool.

Our area of application being pedestrian navigation is the main reason for us to focus our work at the microscopic level. A closer look to the work done at this level will be given next.

1.2.2. MICROSCOPIC MOVEMENT MO-DELS

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 two movement models addressed in this paper can be also be added to the above models.

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 their combining approach 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 or her situation such as age, pursued activity, emotions, degree of disorientation and age or other non-human parameters that affect the 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 using another methodology into two groups. 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 these 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. They are designed to be a function of:

1. Parameters that affect the human movement such as age and activeness. The same previous eleven parameters 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 - directions.

It is important to note that movement in Z-direction is almost always connected strongly to movement in X and Y - directions. So for example, a pedestrian that 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 the stairs area with a high speed in X and Y, then his initial vertical speed will also be high.

The behavioral movement engine developed in [KKRA08] is extended to generate speed and direction in Z-direction. The knowledge of the consumed time allows us to calculate the new position in Z-direction. With this extension we can probabilistically predict movement as a function of behavioral parameters in X, Y and Z-directions at every time step.

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 because the random movement which the model is following 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. Advantage and disadvantages of the model are described in section 2.2.4.

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 can be projected into the 2D projection domain.

Difficulties arise in the stairs area, because of the change in the ground height at each step. The procedure of handling this special area while computing the diffusion matrix is described in section 2.2.2.

For projecting the stairs into the 2D area one needs the 2D top view of the stairs. The top views of different stairs are given in Figure 1.

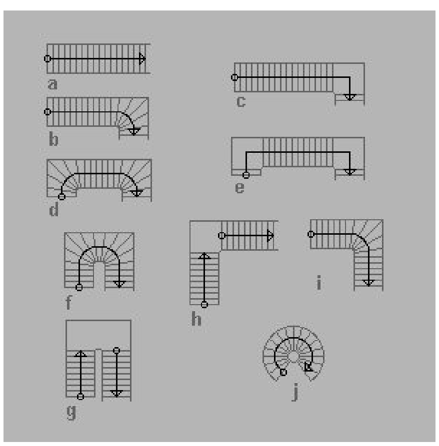

Figure 1: Top views of different stairs

There exist different kinds of stairs (for some examples see Figure 1): stairs without pedestal (a, b, d, f, and i) and with pedestals (c and e), dog-legged stairs (g and h) and newel stairs (j). All the above mentioned stairs (including compact stairs) share a common feature which is the possibility to project them into 2D areas. For the special case of newel stairs each turn of the newel stairs will be handled separately, and this results in a 2D projection for each turn.

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 import 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 stair area as a separate layer. Each layer is the projection of that stairs in 2D. So for example, to compute the diffusion matrix for the 3 level building shown in Figure 2, one has to consider 3 floor plans and 2 plans for the stairs between the levels (we call it x ½ 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.

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-

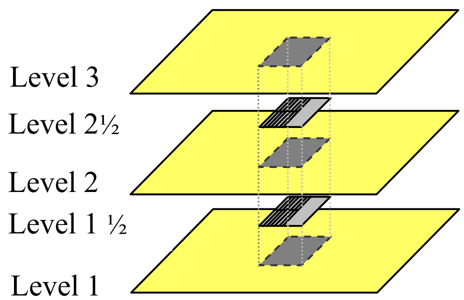

Figure 2: A building with 3 levels and two projections of the stairs ("x ½ level")

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 2).

- A floor that is connected to other floors with the connecting stairs areas at the same location (level 2 in Figure 2). This means that the projection of the connecting stairs areas lies on top of each other or overlaps 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 2).

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 process.

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 (as shown in Figure 3) consists of three steps:

1. The diffusion matrix is first computed for the whole floor plan level 1, where the plan of the stairs area 1 ½ is integrated into the floor plan (see Figure 3, Step 1).
2. The diffusion matrix values for floor plan level 2 with integrated stairs area level 1 ½ is computed. The values of stairs area 1 ½ are also changed (Step 2a). This will influence Step 1 at the next iteration. Actually, the gas is not restricted to only stairs area 1 ½ in the 2nd floor (since the stairs area level 2 ½ is also connected to this floor) so we have to compute the values for floor level 2 with integrated stairs area level 2 ½ (Step 2b). This will result in filling the

stairs area 2 ½ and level 2 with the appropriate values by considering the connection to level 3.

3. The diffusion values for the 3rd floor will be computed with the changed values of level 2 ½. In this step the values of stairs area level 2 ½ are changed (also integrated in level 2) so that the gas can also flow down in the next iteration.

In the following, the concept of the virtual wall will be explained by means of our 3 level building. The virtual wall can be seen as a blue line in Figure 3. We define the entrance to be the beginning of the stairs going up while the exit is the end of them. For instance, if we integrate the stairs area 1 ½ into level 1, the entrance should be open, but the exit should be closed. This is because the entrance is connected to level 1 and the exit is not connected to level 2. And for computing the diffusion matrix of the second floor, the connected exit of the integrated stairs plan 1½ should be open and the not connected entrance should be closed. Respectively, by integrating the stairs plan 2½ into level 2 the entrance should be open and the exit is closed. Finally, by integrating stairs plan 2½ into level 3 means that exit is open and entrance is closed. 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 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

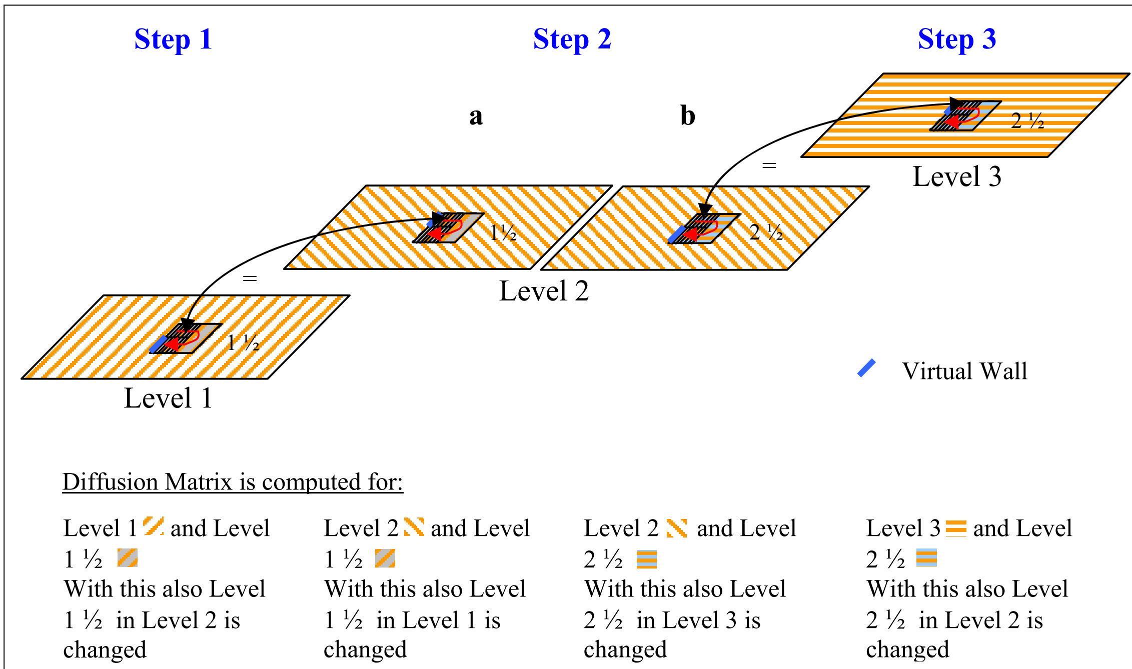

Figure 3: Diffusion Matrix is computed for all 3 layers in 3 steps (3 layers example)

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 in section 2.3.

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 as shown in Figure 4. The combined three dimensional model switches between motions that are non-goal-oriented (section 2.1) or goal-oriented (section 2.2). Details on such a combined movement model can be found in [KKRA08].

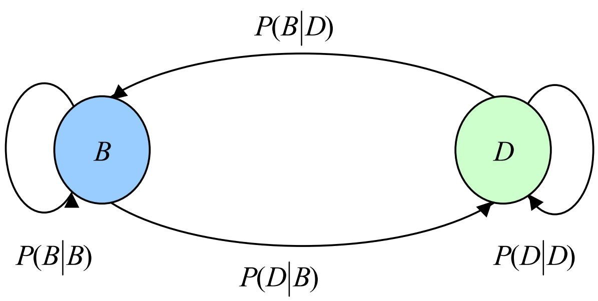

Figure 4: Markov Model used in combining the behavioral (B) and the diffusion (D) movement models

The three dimensional combined model switches between both models randomly with a small transition probability, where each model will be successively used for several time steps before switching to the other one. Actually, following one of the two models for some time before switching to other model complies with a human behavior that tends to exhibit targeted or non-targeted movement for some time before switching.

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

While the pedestrian is outside the stairs area he or she follows the extended Markov model to switch between motion that is more stochastic or goal-oriented. In such case the third dimension calculations are turned off since a normal pedestrian can walk only on surface areas. This saves us some

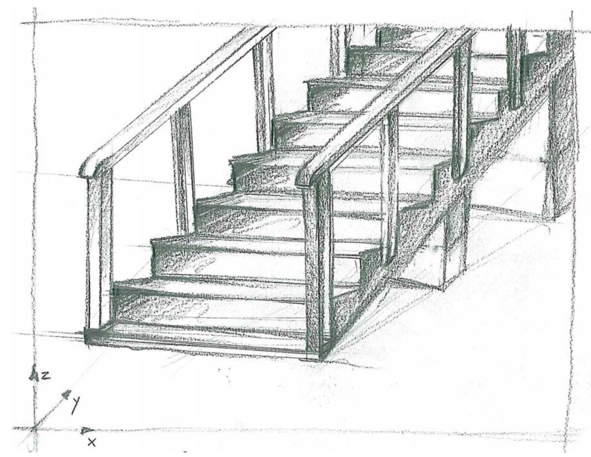

Figure 5: Coordinates of three dimensional stairs

computational costs. The model continuously checks if the pedestrian enters any of the stairs areas in the current floor. 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. Additionally, specific stairs area considerations are applied. Examples of such considerations are the area geometry and the stairs type. 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.

Detecting the pedestrian being in a specific stairs area gives us some important prior knowledge that can be used to parameterize the three dimensional movement model. For example, when undergoing non-targeted motion at a specific stairs area, the activity of the pedestrian (walking up the stairs or down them) and the steepness of the area could be used to draw a more realistic speed.

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 side walls of the stairs are used to prevent our modeled speed of the pedestrian from resulting in a movement that will make the pedestrian cross one of them.

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 time duration.
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.

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 normal Three Dimensional Combined Movement Model without the 3D calculations.

Our pseudo-code formulation for generating a new three dimensional position is:

```
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 (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
      }
      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
         }
    }
}
```

3. SYSTEM DESIGN AND IMPLEMENTATION

Sequential Bayesian Estimators are widely used in estimation problems that are related to noisy and heterogynous 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, a more accuracy and availability could be achieved.

The models are implemented and tested and accordingly some results will be given and discussed in the next section. Qualitative and quantitative analysis of the improvements that our three dimensional movement model brings to the overall estimation process are foreseen for future investigations.

4. SIMULATION RESULTS

Figure 6 shows the diffusion process for calculating the path that is expected to be followed by a pedestrian giving the current position and destination position. Color densities are used to give an indication of the gas concentrations, where dark red represent high densities of the gas compared to dark blue which represents low densities of the gas. Red points represent destination points. The pedestrian's path (white color) will follow the higher densities from the start position till reaching the highest color density (dark red). The virtual wall of the stairs is drawn in blue.

Figure 6a gives the simulation results for the 3D-DMM for a destination point in floor level 1 and a pedestrian starting his walk in level 2. In three floor levels shown in Figure 6a, the stairs area level 1 ½ is integrated in floor level 1 and 2; whereas the stairs area level 2 ½ is integrated in floor level 3. One can see that the path for the pedestrian starts in a room heading toward the stairs area 1 ½ going down to floor level 1. Now the path continues in floor level 1 from the point where the stairs area is connected to it.

The simulation results for a pedestrian starting to walk in floor level 1 and continuing to the destination point in floor level 2 are given in Figure 6b. Here, the stairs area level 1 ½ is integrated in floor level 1 and floor level 2; whereas the stairs area level 2 ½ is integrated in floor level 3. Starting from a room in floor level 1 the pedestrian walks towards the stairs going up to level 2 and continues in level 2 from the point where the stairs area is connected to it.

Finally, Figure 6c gives the results for a destination point located in floor level 3 and a pedestrian starting from floor level 1. The stairs area level 2 ½ is integrated in floor levels 2 and 3; whereas the stairs area level 1 ½ is integrated in floor level 1. The pedestrian will follow the path starting from level 1, continuing via the stairs area level 1 ½ and 2 ½ to reach the destination point in level 3.

From Figure 6 one can see that in a building with more than one level the shortest path to any destination point can still be reached with the 3D-DMM. In addition, the projection of the stairs areas allows us to easily obtain the Z-position of the pedestrian if the X-, and Y-positions are known.

5. CONCLUSIONS AND OUTLOOK

We have presented a human pedestrian motion model that accounts for directed and undirected 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. Our model follows a diffusion process to represent paths that humans typically take to reach a destination. 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, applications can also use the model to calculate shortest paths or to estimate pedestrian densities in building planning.

Future work will focus on quantifying the benefit of an accurate motion model for typical positioning applications with various sensors. Also, a comparison of true human motion (observed from many test subjects over longer time) could be used to verify the probabilistic accuracy of the new model.

6. ACKNOWLEDGMENTS

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7. REFERENCES

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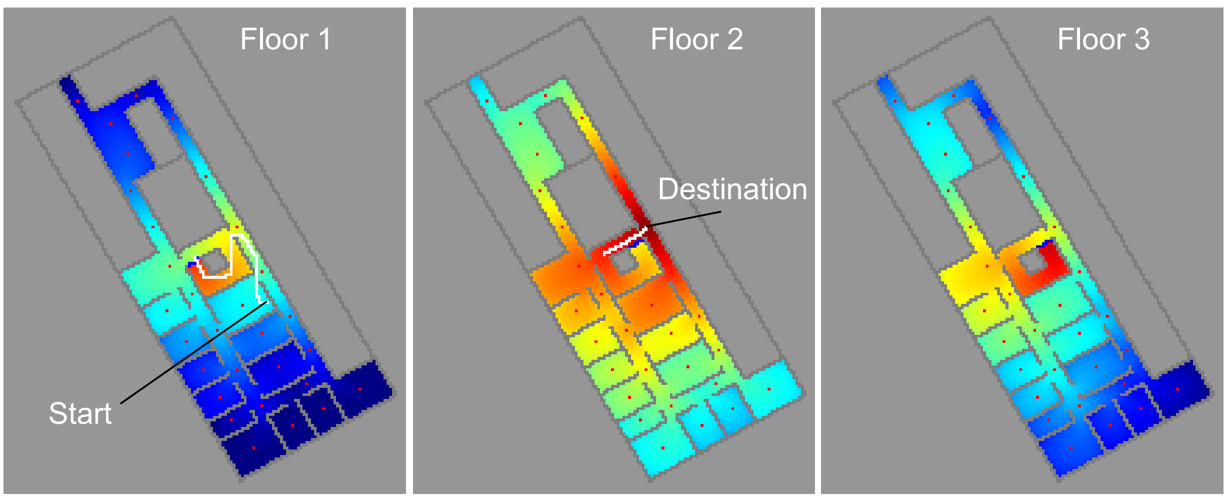
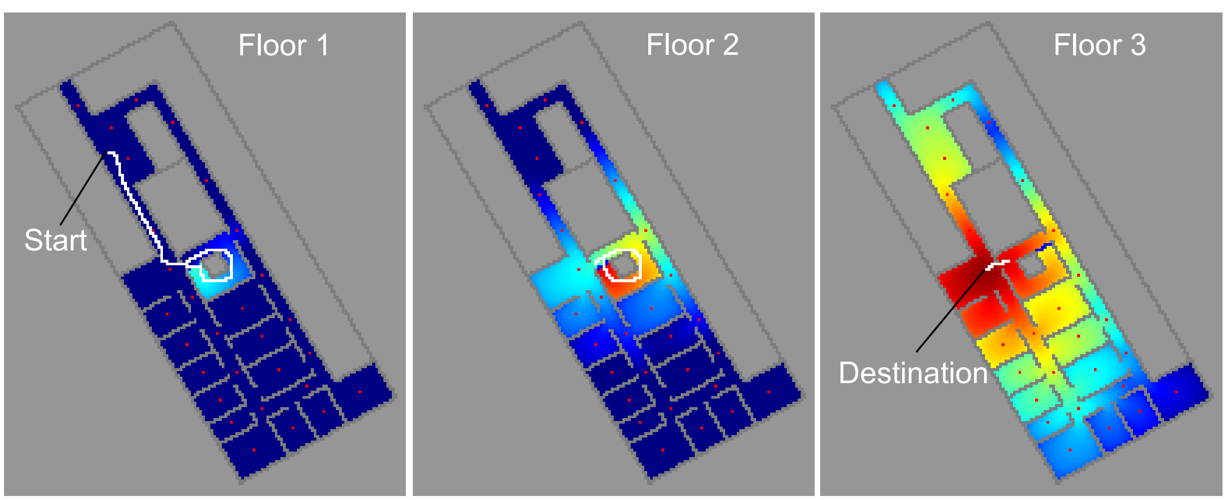
a: Diffusion results for destination point in level 1 and a pedestrian starting in level 2.



b: Diffusion results for destination point in level 2 and a pedestrian starting in level 1.



c: Diffusion results for destination point in level 3 and a pedestrian starting in level 1

Figure 6: Diffusion Movement Model calculations for a 3 floor building

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