A Maps-Based Angular PDF for Navigation Systems in Indoor and Outdoor Environments

Susanna Kaiser*, Mohammed Khider* and Patrick Robertson*
*German Aerospace Center, Weßling, Germany. Email: firstname.lastname@dlr.de

***Abstract*—By incorporating known floor-plans in sequential Bayesian positioning estimators such as Particle Filters (PF), long term positioning accuracy can be achieved as long as the map is sufficiently accurate and the environment sufficiently constraints pedestrians' motion. Instead of using binary decisions to eliminate particles when crossing a wall, a new maps-based angular probability density function (PDF) is introduced in this paper that is capable of weighting the possible headings of the pedestrian according to local arrangements. We will show that the angular PDF will help to obtain better performance in critical multi-modal navigation scenarios.**

***Keywords* — Indoor positioning, Multi-sensor navigation, Particle Filtering, Human Motion Models, Maps.**

I. Introduction

With the development of small, low-cost and light-weight sensors the market for pedestrian navigation arises. Especially indoor navigation is an exciting research and development area that promises new applications for many aspects of our live. A number of approaches are being followed [1][2][3], ranging from high sensitivity Global Navigation Satellite Systems (GNSS), dedicated wireless systems to inertial navigation, as well as various combinations. In this paper we will focus on inertial measurement unit (IMU) based navigation for pedestrians that combines IMU with other sensors. The application is continuous and online meter-level-accuracy positioning with either foot mounted sensors [4] or other suitable forms of pedestrian dead reckoning (PDR) [5][6]. PDR is based on the principle that we can detect and estimate individual steps of a person. A simple step counter can be used to estimate distance travelled [7] and if we estimate heading changes then we can also estimate the relative location change over time. In this work, we perform a true 6 degrees of freedom (DOF) navigation integration, aided during resting phases (e.g. the well known Zero Velocity Update, ZUPT) [4]. Every form of PDR suffers from cumulative errors which might be modeled, for instance, as angular and distance random walks [8]. The result is a random walk error in relative location which implies that the estimated location drifts over time. To handle these drifts a cascaded Bayesian estimation architecture proposed in [9] is used in this paper. Here, a lower Kalman Filter with integrated ZUPT performs PDR and an upper Particle Filter (PF) that can handle floor-plans is cascaded. A Particle Filter usually draws importance samples according to a proposal density function and updates the particle weights – the resulting discrete distribution is an approximation to the true posterior distribution. Resampling the particles after weighting is often done periodically to provide sufficient particle diversity.

When performing Particle Filtering with PDR one typically uses the Likelihood Particle Filter. The Likelihood Particle Filter uses an importance density that is based on the measurement likelihood and uses the state transition prior to weight the particles [10]. In this paper, it draws particles according to a proposal density that reflects the step measurement (PDR). If implemented correctly, it should then weight the particles with the state transition (human motion) model. This paper will address how such a model can be computed given the knowledge of floor plans and other maps.

The posterior distribution of the estimated user position can be multi-modal. In [9][11][12], authors used walls to weight the particles (i.e. particles that cross wall get very low weights). In such case, it has been shown that for instance a single particle that is erroneously remaining in another (larger) room with no effective wall constraints may result in multi-modality and eventually very large positioning errors. This is because this particle will not suffer from running into walls and, therefore, will always receive a high weight, whereas the "correct" particles will be subject to a reduction in their density because a certain proportion of them are eliminated by walls.

In this paper, the proposed location-dependent angular PDF that is based on maps is used to weight particles in a (Likelihood) Particle Filter. With the use of the angular PDF we are computing the particle weights with a more realistic motion model. Our experimental results show that the above mentioned multi modality problem can be successfully addressed. It can also be used in applications when prediction of heading is needed – e.g. in a movement model - with known floor-plans/maps where the possible headings are reduced due to obstacles/walls.

The rest of this short paper is organized as follows: We begin by presenting the multi modality problem. After that we describe the angular PDF that is used in the weighting stage of the Likelihood Particle Filter. After briefly presenting the experimental setup, we show how the proposed model can overcome the failure mode.

II. The Multi Modality Problem

When using no angular PDF, the transition model in the Likelihood Particle Filter is based on binary weighting: if a particle crosses a wall its weight is set to zero, otherwise it is set to one and weighted solely by the likelihood functions of any other non-PDR sensors (such as GPS). This approach only works when the pedestrian is moving within a building with small rooms or corridors, as explained in [13], since in this case all particles suffer comparable elimination rates. With the use of known building layouts to constrain the error in these approaches, particles are being given extremely low weight when they try to cross a wall in the map, and this helps to constrain the particles to walkable areas. However, during the estimation process it may happen that the particle cloud is split into two sub-clouds due to a wall – so they enter two different rooms. If the room size differs, the bigger room has the advantage that particles will not run into walls as fast or as often as inside the more constrained area.

For example, let us consider a scenario where the group of particles is split into two groups due to a wall. Figure 1 shows a floor-plan that contains a large room and an area

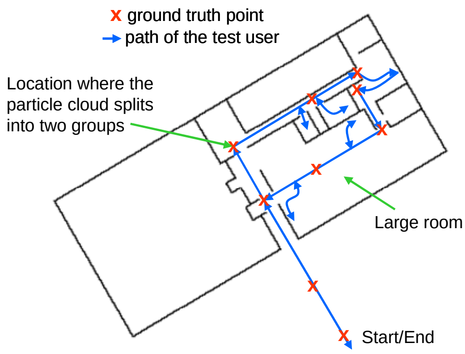


Figure 1. Floor plan of the scenario with one big room and constrained areas

with a small corridor and small rooms. The ground truth track of the pedestrian is given in blue. The user was requested to walk through a predefined specific path starting outdoor with GPS available, walking through the building (3 loops, no GPS) and coming out again. This path passes through several of pre-defined ground truth points (GTP, red crosses) and through many of the rooms in our office building. After the straight walk from outside to inside and turning to the right, during position estimation the particle group splits into two competing groups of particles: One group enters the very large room and the other group enters the small corridor. This is an area with strong constraints such as walls. The second group is actually close to the pedestrian's true location and following her track. Both groups of particles will follow the relative motion of the particles but the second group of particles will suffer a significant reduction in its population – those of its members that explore the PDR error state space but run into walls. The first group, however, will suffer no such losses and will dominate. The second group will more often run into a wall before it has a chance to dominate the particle population. This kind of failure can sometimes be the case especially when there are environments with different kind of constraints. Therefore, in a long-term usage scenario it is only a matter of time before such events may occur, resulting in very large and probably permanent position errors until a second source of location can be obtained (e.g. GNSS, wireless localization). The underlying problem with the aforementioned approaches is the fact that they do not correctly model human motion in buildings. To combat these failures the use of angular PDFs is proposed in this paper.

III. Angular PDFs based on Maps

Our objective is to derive a motion model that assigns a probability to a step of a human being. Since we assume that our PDR is very good at estimating the distance travelled during this step, we can assume that all particles explore steps with very similar distance – hence in this simple model we shall not have to weight according to the distance each particle travels. We shall only have to consider the likelihood of the pedestrian taking a step with respect to the specific direction of that step, originating at the previous location of the particle.

The proposed angular PDFs are derived from a diffusion algorithm based on maps that can also be used as a movement model [13]. Here, the diffusion algorithm taken from [14] is applied, which is extended for using additionally maps and for handling floor-plans in three dimensions [13].

The principle of the computation of the 2D-diffusion matrix based on maps is described in Section A. Section B describes the calculation of the new angular PDFs. Actually the angular PDFs can be pre-computed and stored to reduce the computational effort during position estimation.

A. Calculation of the Diffusion Matrix Based on Maps

The idea of the diffusion algorithm – which is a standard solution for path finding of robots [15] – is to have a source continuously effusing gas that disperses in free space and which gets absorbed by walls and other obstacles. In [14][13], the diffusion model is used with the central assumption to have a source effusing gas which is one of possible destination points. Here, a path finder is needed to find the path to that destination point. In contrary to that, in this paper we assume that the source of the gas is the current waypoint, and we calculate an angular PDF out of the gas distribution. No path finding algorithm is needed anymore and the weighting is independent of the choice of destination points.

The computation of the *diffusion matrix based on maps* can be found in [13]. However, instead of computing the diffusion values for the whole area, we use a sliding square window of size $N_x \times N_y$, where the current waypoint (x_m, y_m) is the middle point of that window:

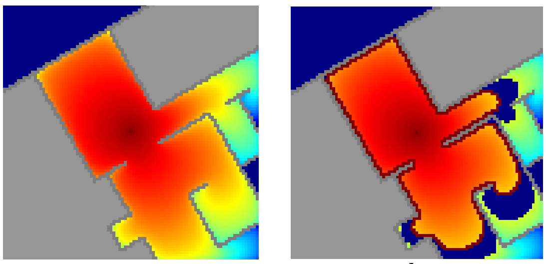
$$\left(x_m, y_m\right) = \left(\left\lfloor \frac{N_x}{2} \right\rfloor, \left\lfloor \frac{N_x}{2} \right\rfloor\right), \tag{1}$$

where $N_x = N_y$ and N_x is odd-numbered. Depending on the grid size and the size of the squared window the resolution of the angular PDF can be varied. The central assumption for defining the angular PDFs is that the possible headings are following the gas distribution, if the current waypoint is the source of the gas.

For each waypoint a so called diffusion matrix $\mathbf{D}_m$ is pre-computed. The diffusion matrix for a particular waypoint contains the values for the gas concentration at each possible waypoint when gas effuses from that source point. The advantage of taking the actual waypoint instead of destination points as the source of the gas is that we can get a weighting function directly from the gas distribution. Another advantage is that the weighting is totally independent from the choice of the location of destination points. In addition, we can restrict the rectangular area to a small area around the actual position, so that the computational effort is much lower. Finally, one can think of storing the PDF values during run-time instead of pre-computing the PDFs for the whole area.

B. Calculation of the Maps Handling Angular PDF

Figure 2a shows the gas distribution (diffusion matrix) from one waypoint within a cutout of a floor-plan. One can see that the gas is restricted through walls to the areas where it can flow. From this diagram we can choose a threshold to get a contour line of the gas distribution. From this contour line we get directly the angular PDF by using the distance to the contour line. When the gas is reaching a wall, the contour ends at the wall and the distance is equal to the distance to the wall. Figure 3 shows the polar diagram of the angular PDF. The weight is higher on the ways where the persons may walk. Since it is possible to stay in front of a wall, a small distance is applied for the directions to the wall in the case that the current position is close to the wall. Additionally, when particles cross a wall, their weight is set to a very small value.



a. b.

Figure 2. a. Diffusion matrix for a square area and the current waypoint in the middle; b. Contour line (dark red) of the diffusion values

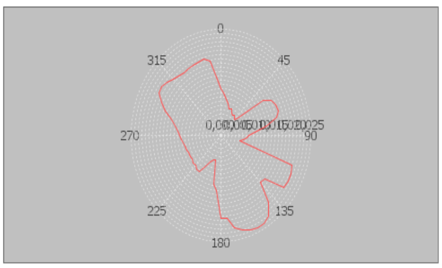


Figure 3. Polar Chart of the angular PDF

Details of the calculation of the angular PDF are given next. The contour-line of the diffusion matrix represents our angular PDF. Therefore, we have to determine this contour-line first. Here, we specify for the diffusion area a set $\mathbf{C}$ of N_c contour-line points:

$$\{c_1,\ldots,c_{N_c}\}=\{(x_1,y_1),\ldots,(x_{N_c},y_{N_c})\}. \qquad (2)$$

The contour line points can be obtained by checking all the diffusion values to be below a certain threshold T. If a diffusion value at (k,l) is below that threshold:

$$d_{k,l} < T \quad , \qquad (3)$$

and the diffusion value of at least one neighboring point (direct neighborhood) is greater than the threshold T:

$$d_{k+o,l+p} > T \quad \forall o,p:\ o=-1,0,+1, \quad p=-1,0,+1, \quad o\neq p\neq 0, \qquad (4)$$

then, the position (k,l) is part of the set of contour-lines:

$$C(k,l)\in\mathbf{C}. \qquad (5)$$

Walls are included in this computation since for a point on the wall the following equation holds:

$$d_{k,l}=0 \quad if \quad l_{k,l}=0 \ . \qquad (6)$$

Figure 2b shows the contour line of the diffusion values marked in dark red (T was set to 0.0001).

The value of the angular PDF for an angle α is obtained via the distance of the current waypoint (x_m,y_m) to the contour-line point that lies in the direction of that angle α. Here, α is the absolute angle when drawing a line from the contour point to the waypoint (x_m,y_m) in a Cartesian coordinate system where (x_m,y_m) represents the middle point. The distance b between the current waypoint and the point of the contour line (k,l) is defined as:

$$b_{C(k,l)}=\sqrt{(x_m-k)^2+(y_m-l)^2}\ . \qquad (7)$$

The values for the non-normalized weighting function $\tilde{w}$ are obtained by the maximum of possible distances to points of the contour-line with a specified angle:

$$\tilde{w}(\alpha)=\max_{\substack{C(k,l)\\ \varphi(k,l)=\alpha}} b_{C(k,l)}, \qquad (8)$$

where $\varphi(k,l)$ is the absolute angle between the contour point $C(k,l)$ and the actual waypoint (x_m,y_m).

Additionally, it is checked if the direct line of the waypoint to the contour line points crosses a wall. Those contour line points that cross a wall are not considered in the computation of the angular PDF, since the directions to points behind a wall should not be favored.

Finally, the weighting function is normalized:

$$w(\alpha)=\frac{\tilde{w}(\alpha)}{\sum_{\beta=0}^{2\pi}\tilde{w}(\beta)}. \qquad (9)$$

In our simulation we used discrete values for the angle α. The angle spacing was 5° and we had 72 different values for computing the weighting function. These values seemed to be enough to obtain a smooth weighting function.

To adapt the histogram to the speed of the pedestrian the following equation is applied to the weight $w(\alpha)$:

$$w'(\alpha)=w(\alpha)^S, \qquad (10)$$

where S is the step-length of the particle. With this, more weight is given to smaller steps and less weight is applied to large steps. This is done because weighting is multiplicative over time, and the weight change (ratio) should be normalized to a given distance travelled (here corresponding to 1 meter, when S = 1.) Many small steps, when adding to 1 meter will have the same weight change, assuming that the angular PDF does not change over the step.

IV. EXPERIMENTAL SETUP AND RESULTS

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 transition models.

The Sequential Bayesian Positioning Estimator that was used to evaluate the performance of our weighting function was based on a Particle Filter fusion engine and used the following sensors: commercial GPS, electronic compass and a foot-mounted IMU with ZUPTs [9].

Whenever the test user passed across one of the GTPs (see Figure 1), the estimated position at that point was compared to the true position. The GTPs were carefully measured to the sub-centimeter accuracy using a tachymeter (Leica Smart Station TPS 1200). Errors between the true and estimated pedestrian positions were recorded with and without the use of the angular PDFs.

To illustrate the benefits of the use of the angular PDFs the scenario with different wall constraints described in chapter II is used, where the particle cloud splits into two groups of particles during estimation. When binary decisions are used, the correct particle cloud is eliminated due to the wall constraints in the restricted (correct) area and the wrong cloud survives. In contrary to that, the use of the weighting function compensates the loss of particles due to wall crossings. As time elapses, the correct particles cloud is continuously rewarded and re-sampling results in eliminating the wrong cloud.

Figure 4 shows the average position error for 100 simulation runs of the investigated scenario. Comparing the use of no angular PDF (red curve) with the use of the angular PDF (blue curve), we can see that after the 4^{th} GTP the particle split into two groups and the correct group survives when using the angular PDF for weighting. When using only walls to weight the particles (binary weighting), the correct particle cloud was eliminated in all simulation runs and the positioning error became large. Since in both cases the particle cloud is very large within the large room – the correct groups of particles enters the large room through the corridor and the wrong cloud stayed inside the large room due to the wall constraints -, the error of the position of the particles is similar in both cases at GTP 8, but the heading drift is larger with the erroneous wrong cloud so that the position error gets higher again due to position estimation failures. As expected, the scenario where the maps based weighting function is used has shown much lower average position error compared to the case where binary weighting from wall crossings is used.

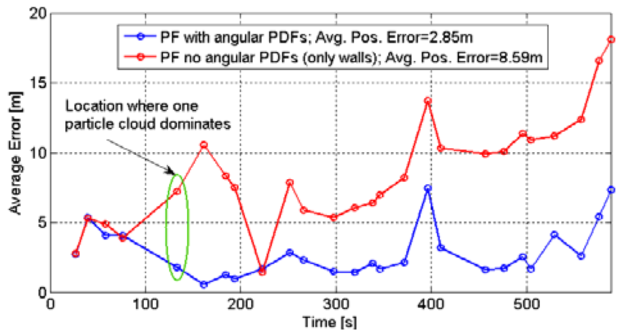


Figure 4. Average position error for two starting groups of particles

V. CONCLUSION

In this short paper we presented a transition model for pedestrians that use a known building layout to construct an angular PDF for a pedestrian's step direction. We have demonstrated that a simple Particle Filter that only uses the knowledge of walls to constrain particles can diverge if the particles distribution is multi-modal and a competing, erroneous particles group is in an area with few limiting wall in their vicinity. It has been shown that weighting with the angular PDF performs better than using no transition model when there are two groups of particles. Further work should focus on more data sets, on different wall situations and on the use of different accessibility levels in indoor and outdoor environments.

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