Application of Particle Filters for Indoor Positioning Using Floor Plans

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Abstract— **This paper presents a numerical approach to the pedestrian map-matching problem using building plans. The proposed solution is based on a sequential Monte Carlo method, so called particle filtering. This algorithm can be adapted for implementation on real-time pedestrian navigation systems using low-cost MEMS gyroscopes and accelerometers as dead-reckoning sensors. The algorithm reliability and accuracy performance was investigated using simulated data typical for pedestrians walking inside building. The results show that this map-aided dead reckoning system is able to provide accurate indoor positioning for long periods of time without using GPS data.**

Keywords- pedestrian navigation, map-matching, sequential Monte Carlo method, particle filtering

I. INTRODUCTION

High-performance autonomous pedestrian dead-reckoning (PDR) systems usually include inertial sensors to calculate position of the user. These systems don't rely on GPS signals and preinstalled infrastructure such as RF beacons, Wi-Fi routers, ultrasonic transmitters etc. It is well known that position error in PDR systems grows with time. One way to curb the divergence of position errors is to use building floor plans. This process of data fusion from positioning system with maps is usually called map-matching. The goal of map-matching is to exploit prior information contained in a building floor plan. However, incorporating this information within the conventional Kalman filtering framework is not an easy task. The reason is that floor plans represent a constraint which leads to highly non-Gaussian posterior densities that are difficult to represent accurately using the conventional techniques.

In this paper we propose a numerical approach to a pedestrian map-matching problem solution based on recursive implementation of Monte-Carlo based statistical signal processing, also known as particle filtering. The basic principle is to use random samples (also referred to as particles) to represent the posterior density of the pedestrian position in a dynamic state estimation framework where floor plan information is used. Since particle filters have no restrictions on the type of models and noise distribution, the constraints on user trajectory in form of walls, doors, passages and staircases which tend to be nonlinear in nature can be accurately modeled. Additionally, a particle filter is able to capture multi-modal distributions which tend to occur when there is uncertainty in which part of the building the user is on. By carrying forward multiple possibilities, the particle filter is able to quickly adapt if an initial guess at the user's location is found to be incorrect. Another large benefit of a particle filter for this application is that it provides a natural way for building floor plan information to be incorporated into pedestrian position estimation. One approach is by applying direct constraints on the state vector which affect each particle.

Map-matching algorithms are widely used for car navigation under the assumptions that car is travelling on the road and non-holonomic constraint is valid. In the case of pedestrian navigation the situation is not so simple. A person can move not only on the roads but across a much more diverse area. In the case of indoor pedestrian navigation the movement of a person is restricted by the walls of a building. If it is known that the person is located in a certain room of the building then the position of the PDR system can be updated.

In this paper, we propose a probabilistic, numerical approach to the map-matching problem. The proposed solution is based on recursive implementation of Monte-Carlo based statistical signal processing known also as particle filtering [1]-[4]. The basic principle is to use random samples (also referred to as particles) to represent the posterior density of the pedestrian position in a dynamic state estimation framework where building plan information is used. Since particle filters have no restrictions on the type of models and noise distribution, the velocity and heading measurement errors can be modeled accurately.

The major advantage of a particle filter for this particular application is that it provides a natural way for building plan information to be incorporated into pedestrian position estimation, by applying the direct constraint on the state vector (which affects each particle) [5][6]. Another advantage is its ability to capture multi-modal distributions which tend to occur when there is uncertainty in which part of the building the user is on. By considering multiple candidate roads, the particle filter is able to quickly adapt if an initial guess at the proper road is found to be incorrect.

This paper presents simulation results typical for pedestrians walking inside building. The position measurements imitated the position calculated by pedestrian dead-reckoning system using wearable inertial sensors. These measurements were combined with the floor plan to calculate the position of the person as he walked inside the building. The results shown in this paper demonstrate that the proposed particle filter approach is reliable and accurate. It is able to correct large errors in dead reckoning position by applying the map constraints.

II. PROBLEM STATEMENT

The objective of map-matching is to estimate recursively the position of the user from a set of measurements. This problem can be stated as estimation of the sequence of states $x_{0:k} = \{x_0, \cdots, x_k\}$ given the series of observations $y_{1:k} = \{y_1, \cdots, y_k\}$ subject to the system model, measurement model, and constraints on the user movement given in form of the building plans. The prior probability $p(x_0)$ is assumed to be known. The state is a user point position. The system model is based on a constant velocity model in form of the following dead-reckoning equations:

$$x_{k+1} = \begin{bmatrix} P^N_{k+1} \\ P^E_{k+1} \end{bmatrix} = x_k + L_k \cdot \begin{bmatrix} \cos\psi_k \\ \sin\psi_k \end{bmatrix} \tag{1}$$

where P_N, P_E are the user coordinates, L_k is the distance travelled from time instance t_k to t_{k+1} and ψ_k is the stride azimuth. It is assumed that a position and heading measurement is available to the system (for example, from a dead-reckoning solution).

III. ALGORITHM FOR SOLVING THE PROBLEM WITHIN THE FRAMEWORK OF PARTICLE FILTERING

This problem can be solved within the framework of Bayesian estimation theory. According to the Bayesian view, the posterior probability density function (pdf) $p(x_{0:k}|y_{1:k})$ contains all the statistical information available about the state vector x_k, based on the information in the measurements $y_{1:k}$. The algorithm is derived from the recursive decomposition of $p(x_{0:k}|y_{1:k})$ based on "Bayes rule" and "Law of total probability"

$$p(x_{0:k}|y_{1:k}) = \frac{p(y_k|x_{0:k}, y_{1:k-1})p(x_{0:k}|y_{1:k-1})}{p(y_k|y_{1:k-1})} = \frac{p(y_k|x_{0:k}, y_{1:k-1})p(x_k|x_{0:k-1}, y_{1:k-1})p(x_{0:k-1}|y_{1:k-1})}{p(y_k|y_{1:k-1})} \tag{2}$$

If the probabilistic model of the transitional density is described by a Markov process of the first order such that $p(x_k|x_{0:k-1}, y_{1:k-1}) = p(x_k|x_{k-1})$ then the calculation of $p(x_{0:k}|y_{1:k})$ can be simplified. It is calculated recursively as

$$p(x_k|y_{1:k}) = \frac{p(y_k|x_k)p(x_k|x_{k-1})p(x_{k-1}|y_{1:k-1})}{p(y_k|y_{1:k-1})} \propto p(y_k|x_k)p(x_k|x_{k-1})p(x_{k-1}|y_{1:k-1}) \tag{3}$$

The recursion (3) cannot be computed analytically but it can be calculated using the sequential Monte Carlo approximation. The key idea underlying the sequential Monte Carlo methods is to represent the probability density function by a finite set of sample trajectories (particles) and their associated weights $\{x^{(i)}_{0:k}, w^{(i)}_k\}$.

The generation of samples from $p(x_{0:k}|y_{1:k})$ is performed in two steps: prediction and update [2][3]. In the prediction step, each path $x^{(i)}_{0:k-1}$ is grown with one step to obtain $\tilde{x}^{(i)}_{0:k}$ by sampling from the proposal density function $p(x_k|x^{(i)}_{k-1})$. In the update step, each sample path is associated with a weight, which is proportional to the likelihood of the measurements

$$w^{(i)}_k \propto w^{(i)}_{k-1} p(z_k|x^{(i)}_{k-1}) \tag{4}$$

The resulting set of weighted trajectories $\{x^{(i)}_{0:k}, w^{(i)}_k\}$, i=1, …, N, with normalized weights provides an approximation to the distribution $p(x_{0:k}|y_{1:k})$. Based on the discrete approximation of the posterior pdf, an estimate of the "best" trajectory at step k+1 can be obtained. The path with a maximum weight provides an approximation to the MAP estimate. The mean represents a Monte Carlo approximation of the posterior pdf expectation.

IV. TRANSITIONAL PRIOR AND LIKELIHOOD

The proposal transitional prior is based on the dead-reckoning equations (1). In most of cases, an additive zero-mean Gaussian noise in the stride length and stride azimuth measurements can be a good approximation. Then the particles can be simply sampled from the transitional prior described by Eqn 1 where the stride length $L^{(i)}_k$ and azimuth $\psi^{(i)}_k$ for i-th particle are sampled from the normal distributions $\mathrm{N}(L_k, \sigma_L)$ and $\mathrm{N}(\psi_k, \sigma_\psi)$ respectively. The expectations L_k and ψ_k are calculated based on the data from the inertial sensors. The standard deviations σ_L and σ_ψ replicate the errors of the original uncorrected dead reckoning solution. They are time varying and assumed to be known. The weights of the particles are updated using the recurrent formula (4). In this formula, $p(z_k|x^{(i)}_{k-1})$ is a likelihood calculated for each particle based on the proximity between the position fix and the particle, and the difference between the measured heading and the heading associated with this particle. The likelihood is calculated according to

$$p\left(z_k \middle| x_{k-1}^{(i)}\right) \propto \exp\left\{-\frac{\left\|x_{k-1}^{(i)} - x_{meas}\right\|^2}{2\sigma_{pos}^2}\right\} \tag{5}$$

where $x_{k-1}^{(i)}$ is the i-th particle coordinate, x_{meas} is the measured user position, σ_{pos}^2 is the position measurement variance. In addition to the measurement update the condition of not crossing the walls is also checked. The path increment for each particle $x_{k+1}^{(i)} - x_k^{(i)}$ is checked for crossing the walls. The particle is downweighted by a factor of 100 if it crossed the wall according to

$$w_k^{(i)} = \begin{cases} 0.01 \cdot w_k^{(i)}, & \text{if the wall is crossed} \\ w_k^{(i)}, & \text{otherwise} \end{cases} \tag{6}$$

These importance weights are normalized according to

$$\tilde{w}_k^{(i)} = w_k^{(i)} \Big/ \sum_{j=1}^{N} w_k^{(j)} \tag{7}$$

Resampling is required in particle filters to avoid the degeneracy problem. According to [2], a suitable measure of degeneracy is the effective sample size N_{eff} that can be estimated by

$$\hat{N}_{eff} = \frac{1}{\sum_{i=1}^{N}\left(w_k^{(i)}\right)^2} \tag{8}$$

Whenever N_{eff} falls below some pre-defined threshold the resampling is required. In our work the systematic resampling was used. A new set of samples is drawn with replacement from the previous set with the probability of a sample being drawn proportional to its weight. The final set represents the new posterior, but now the samples are equally weighted. During the resampling step, unlikely samples are omitted and samples with high probability are multiplied. To avoid ending up with only a few different samples, noise is introduced during the prediction step to improve the diversity. If resampling is applied at each update step the relationship in (4) simplifies to:

$$w_k^{(i)} \propto p\left(z_k \middle| x_{k-1}^{(i)}\right) \tag{9}$$

V. Simulation Results

This section presents simulation results. To demonstrate the performance of the proposed algorithm the building floor plan, pedestrian trajectory and associated position measurements were simulated. The performance of the particle filter was evaluated when the pedestrian was moving along the trajectory shown in fig. 1. In the chosen scenario while a pedestrian moves through a building, the position, heading and speed are calculated by the dead reckoning system based on

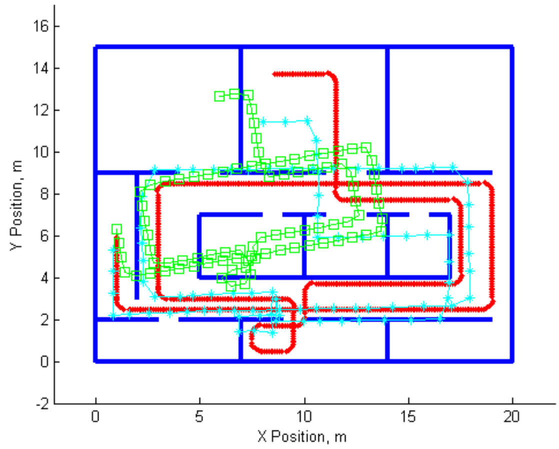

Figure 1. *Walking test simulation. The walls of the building are shown in blue. The true trajectory is shown in red. The current user position is at the end of the red line. The dead reckoning computed position is shown in green. The particle filter solution is shown in cyan.*

inertial sensors data only. The initial position is assumed to be known with some error corresponding to the dead reckoning system position error. No source of absolute position information such as GNSS is used. The only source of additional information available to the particle filter is the building floor plan. It is also assumed that the user is located inside the specified building.

The simulated errors of dead reckoning solution are assumed to be large: the heading error is 10°, the step length estimation error is 30% of travelled distance. Such large errors may correspond, for example, to using magnetometer and simple pedometer as the dead reckoning sensors. The accuracy of the dead reckoning solution is constantly monitored. The variance of position error in measurement update is changing to match the errors of the dead reckoning solution.

The particle filter calculations are based on 100 particles. The dead reckoning solution is used as the position measurement for the particle filter. The distribution of particles at different parts of the test trajectory is shown in fig. 2. The particle filter solution is represented by the weighted mean of the particles shown by the magenta asterisk.

From fig. 1 and 2 it is clear that the knowledge of floor plan can improve the accuracy of position estimation calculated by the dead reckoning system. From these results, it can be seen that the accuracy of particle filter solution is approximately equals to the width of the corridors and doorways. Therefore the approximate limit on the possible position accuracy of this approach is set by the size of the rooms and level of floor plan details. Some particles succeeded to cross the walls because the penalty for crossing walls is not the complete elimination of this particle but only its downweighting. The factor by

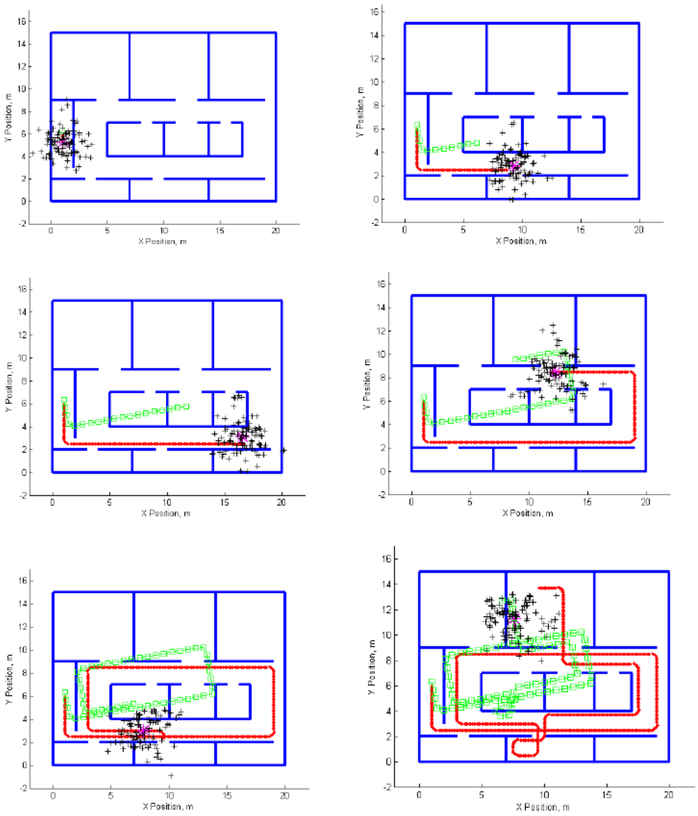

Figure 2. *Map-matching algorithm performance during the test. (Green squares: original, uncorrected DR solution; Black points: particle locations; Magenta asterisk: weighted mean of particles; Red dots - true location)*

which the particles are downweighted is a design parameter that can be adjusted to have the optimum performance in terms of robustness to the errors in building plans and variance of the position estimation error.

VI. Conclusions

This paper has shown how the map-matching algorithm can improve pedestrian navigation system performance. This becomes very important when the position calculation is based on dead reckoning sensors. The dead reckoning solution can be corrected occasionally. This correction can be calculated based upon map matching solution. If the pedestrian's movement is suitable it is possible to keep small position errors for long periods of time. The example shows that the position errors of map aided dead reckoning navigation system can be kept bounded as opposed to the unbounded error growth of the conventional dead reckoning.

The performance of the proposed particle filter based map-matching algorithm depends on the following factors:

- Pedestrian's movement. The long walking path covering different rooms of the building improves the accuracy of position estimation.
- Size of the rooms and hallways affects the accuracy. The smaller the dimensions the better accuracy can be achieved.

The particle filter performance can be adjusted by changing ground speed noise and position and heading variances. Increasing ground speed noise improves the particles diversity. Position and heading variances have to match approximately the position and heading measurement errors of onboard sensors. Using inertial measurements and building plans only makes the process of positioning entirely autonomous and gives promising results. This method of positioning can be applied to many pedestrian navigation tasks. In particular, it suits the needs of fire-fighters and rescue services. The algorithm is suitable for real-time implementation on personal navigation devices.

The future efforts in this research will be focused on improvement of the dead reckoning solution and modeling of more diverse pedestrian movements including vertical movements (e.g. taking the stairs). Future experiments will determine if this approach has any significant value for paths through larger spaces such as parking garages or warehouses.

References

[1] Doucet A., Godsill S., and Andrieu C., "On sequential Monte Carlo sampling methods for Bayesian filtering", *Statistics and Computing* (2000) **10,** 197–208

[2] Ristic, B.; Arulampalam, S.; Gordon, N. *Beyond the Kalman Filter: Particle Filters for Tracking Applications*. Artech House, 2004.

[3] Arulampalam, M. S., Maskell, S., Gordon, N., and Clapp, T., "A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking," IEEE Transactions on Signal Processing, vol. 50, no. 2, Feb. 2002.

[4] Gustafsson, F., Gunnarsson, F., Bergman, N., Forssell, U., Jansson, J., Karlsson, R., and Nordlund, P.-J., "Particle filters for positioning, navigation, and tracking," IEEE Transactions on Signal Processing, vol. 50, no. 2, Feb. 2002.

[5] Widyawan, M. Klepal, and S. Beauregard, "A backtracking particle filter for fusing building plans with PDR displacement estimates," in Proceedings of the 5th Workshop on Positioning, Navigation and Communication, 2008, WPNC08, Hannover, Germany, Mar. 2008.

[6] S. Beauregard, "Omnidirectional pedestrian navigation for first responders," in Proceedings of the 4th Workshop on Positioning, Navigation and Communication, 2007, WPNC07, Hannover, Germany, Mar. 2007, pp. 33–36.

[7] B. Krach and P. Robertson, "Integration of foot-mounted inertial sensors into a Bayesian location-estimation framework," in Proceedings of the 5th Workshop on Positioning, Navigation and Communication, 2008, WPNC08, Hannover, Germany, Mar. 2008.

[8] M. Khider, S. Kaiser, P. Robertson, and M. Angermann, "A novel movement model for pedestrians suitable for personal navigation," in Proceedings of the Institute of Navigation National Technical Meeting 2008, San Diego, California, USA, Jan. 2008.