A Backtracking Particle Filter for Fusing Building Plans with PDR Displacement Estimates

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***Abstract*—It is known that Particle Filter and Map Filtering techniques can be used to improve the performance of positioning systems, such as Pedestrian Dead Reckoning (PDR). In previous research on indoor navigation, it was generally assumed that detailed building plans were available. However, in many emergency / rescue scenarios, there may be only limited building plan information on hand. The purpose of this paper is to show how a novel Backtracking Particle Filter (BPF) can be combined with different levels of building plan detail to improve PDR performance.**

We use real PDR stride length and blunder-prone stride azimuth data which were collected from multiple walks along paths in and out of a small office building. The PDR displacement data is input to the BPF estimator that in turn uses the building plan information to constrain particle motions. The BPF can take advantage of long-range (geometrical) constraint information and yields excellent positioning performance (1.32 m mean 2D error) with detailed building plan information. More significantly, this same filter using only external wall information produces dramatically improved positioning performance (1.89 m mean 2D error) relative to a PDR-only, no map base case (8.04 m mean 2D error).

This effect may very well occur for many other realistic wall layouts and path geometries. Moreover, this result has a substantial practical significance since this level of building plan detail could be quickly and easily generated in many emergency instances.

***Index Terms*—indoor positioning, backtracking particle filter, pedestrian dead reckoning, map filtering**

I. Introduction

Positioning and navigation for firefighters and other first-responder is a mission-critical function. Several viable techniques currently exist for outdoor positioning. GPS positioning can satisfy outdoor positioning requirements in many instances. However, the GPS system does not work reliably indoor since its signal suffers from the attenuation, reflection and refraction from buildings and walls. Moreover, outdoors is not where the critical needs lie: a large fraction of first responder injuries and deaths occur inside buildings, typically when these are on fire and/or structurally compromised [1]. Therefore there is still a need for high-performance indoor positioning for professional user such as firefighter and other first-responder [2].

Pedestrian Dead Reckoning (PDR) has emerged as one of the alternative technologies for indoor positioning and navigation. PDR is often broadly categorized as an infrastructure-less positioning technology and has an ad-hoc nature that makes it suitable for rescue/emergency scenario. It is a relative navigation technique in which successive displacements, i.e. strides, from a known starting position are added up. Recent field trial [3] shows that PDR technique can achieve interesting performance. However, this technique still lacks robustness, particularly with regards to heading. This shortcoming will cause a skewed path over time and produce position estimates that might not be consistent with the building layout (e.g. resulting paths cross walls, floors or other obstacles). It is known that Particle Filter and Map Filtering techniques can alleviate this problem [4]. PDR positions can be forced to adhere building plans.

The aim of this paper is to propose a framework for fusing building plans and PDR motion using a Particle Filter. A novel variant of the Particle Filter, called the Backtracking Particle Filter (BPF), is decribed and evaluated with real PDR displacement data as input. For many emergency/rescue scenarios, there is often only limited building plan information at hand. For example, only external wall outlines might be available from aerial photographs or cadaster databases. Escape plans posted at the entrances in many buildings show only approximate exit door and stairwell locations with little or no detail for individual rooms. Therefore, the fusion framework is also evaluated against different levels of building plan detail.

The remainder of the paper is organized as follow. In the Section II, a PDR based positioning system is briefly introduced. The filtering algorithm and the novel Backtracking Particle Filter will be proposed in the Section III. Section IV will briefly describe the tools and experiments conducted. Section V will present the results of the experiments. Finally section VI will conclude the paper.

II. Foot-Inertial Pedestrian Dead Reckoning

In the foot-inertial approach to pedestrian navigation, the distance between footfalls is estimated from 3D acceleration and orientation measurements sensed directly at the foot. An inertial measurement unit (IMU), containing tri-axial accelerometers, rate gyros and magnetometers, is solidly

Fig. 1. The orange XSens motion sensor is held on by the shoe laces.

attached to, or mounted in, footwear (Figure 1). Standard strap-down mechanization equations were applied to the IMU measurements. Very briefly, a rotation matrix that brings the sensor (or body) coordinate system to the world coordinate system is estimated. Then the accelerations in the body frame are rotated to the world frame with this matrix and the resulting accelerations are double integrated to yield a displacement in the world frame. The velocity is held to zero when the accelerations and rate gyro measurements drop below empirically determined values. Our approach is similar to that taken in [5][6][7] and elsewhere.

We did not attempt to write our own very complex, adaptive quaternion/Kalman sensor fusion filter (as done in [5]) for estimating the rotation matrix or sensor biases. Instead, we used the software API that came with the sensor to get the orientation matrix. Given the nature of this adaptive sensor fusion filter and of the footfall-to-footfall inertial calculations, the path heading does not show the smooth drift pattern typical of dead reckoning systems. We have observed over many experiments that when the azimuth (heading) change between strides is small, the uncertainty in the heading change in small. In other words, straight segments are mostly correct. On the other hand, when a large heading change is measured, the uncertainty is large. We therefore put less confidence on measured turns. This observation is used in the particle transition function described below. A more detailed analysis of this phenomenon will be presented in a future publication.

Even if a better sensor fusion filter were used, we argue that significant heading errors will likely still occur when such a PDR system is deployed in the real world. The extreme operating conditions (high temperatures, in particular) will perturb the IMU. Consequently, the compensation approach using the BPF and minimum building plan information presented in this paper is still pertinent.

III. Filtering Algorithm

To define the problem during location estimation, the target state x_t and measurement z_t evolves according to the following discrete-time stochastic model [8]:

$$\mathbf{x}_t = f_{t-1}(\mathbf{x}_{t-1}, \mathbf{n}_{t-1}) \quad (1)$$

$$\mathbf{z}_t = h_t(\mathbf{x}_t, \mathbf{e}_t) \quad (2)$$

where where f_{t-1} and h_t are known, possibly non-linear function, $\mathbf{n}_{t-1}$ and $\mathbf{e}_t$ are independent and identically distributed noise. In the case of indoor localization, the problem is to recursively quantify the state $\mathbf{x}_t$ at time t given the all available measurement data $\mathbf{Z} \triangleq \{\mathbf{z}_i, i = 1, ..., t\}$ up to time t. From a Bayesian perspective, it is required to construct the posterior pdf $p(\mathbf{x}_t|\mathbf{Z}_t)$. The construction of the posterior pdf is achieved through the Chapman-Kolmogorov equation and Bayes' Rule[9]:

$$p(\mathbf{x}_t|\mathbf{Z}_t) = k^{-1} p(\mathbf{z}_t|\mathbf{x}_t) \int p(\mathbf{x}_t|\mathbf{x}_{t-1}) p(\mathbf{x}_t|\mathbf{Z}_{t-1}) dx_{\mathbf{t-1}} \quad (3)$$

with the normalizing constant k:

$$p(\mathbf{z}_t|\mathbf{Z}_{t-1}) = \int p(\mathbf{z}_t|\mathbf{x}_t) p(\mathbf{x}_t|\mathbf{Z}_{t-1}) d\mathbf{x}_t \quad (4)$$

$p(\mathbf{z}_t|\mathbf{x}_t)$ represents the likelihood function, $p(\mathbf{x}_t|\mathbf{x}_{t-1})$ is the transition pdf and $p(\mathbf{x}_t|\mathbf{Z}_{t-1})$ is the previous posterior distribution.

Knowledge of the posterior density enables an estimation to be made, for instance to obtain minimum mean-square error of $\mathbf{x}_t$.

$$\hat{\mathbf{x}}_t^{MMSE} = \int \mathbf{x}_t p(\mathbf{x}_t|\mathbf{Z}_t) dx_t \quad (5)$$

The aforementioned equation is in reality often hard or impossible to solve analytically, and in particular when the measurement equation is non-linear or the noise distribution is non-Gaussian. One of the emerging sub-optimal solutions is the Particle Filter [9][10]. In this paper we propose a novel variation of the Particle Filter method called the Backtracking Particle Filter which refines the state estimation based on state history.

A. Particle Filter and Map Filtering

Particle Filtering is a technique that implements a recursive Bayesian filter using the Sequential Monte-Carlo method. It is particularly good for dealing with non-linear and non-Gaussian estimation problems. It is based on a set of random samples with weights, called particles, for representing a probability density. The Particle Filter directly estimates the posterior probability density function (pdf) of the state using the following equation [9]:

$$p(\mathbf{x}_t|\mathbf{Z}_t) \approx \sum_{i=1}^{N} w_t \delta(\mathbf{x}_t - \mathbf{x}_t^i) \quad (6)$$

where $\mathbf{x}_t^i$ is the i-th sampling point or particle of the posterior probability and w_t^i is the weight of the particle. Figure 2 gives illustrates how a particle filter can used for tracking a person. It shows a sequence of posterior distributions, likelihood functions and state estimates at $t = 1$s, $t = 20$s and $t = 30$s.

For indoor positioning, building plans are very useful information that can be used to enhance location accuracy and reduce uncertainty of walking trajectories. Particle Filters can take into account building plan information during the indoor positioning process with a technique called Map Filtering [4].

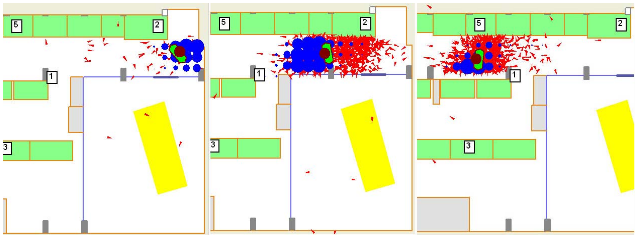


Fig. 2. Sequence of particle posterior distributions at $t = 1s$,$t = 20s$, and $t = 30s$. The blue circles represent the likelihood function

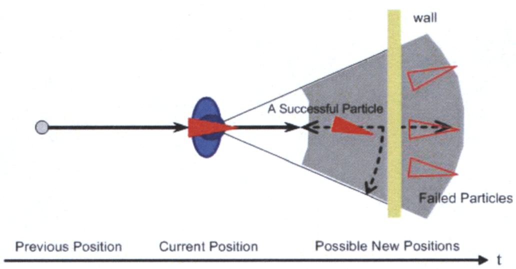


Fig. 3. Particle Transition Near Obstacles: If a particle tries to move across walls or other obstacles defined in the map, it will be killed off.

Map Filtering implements a fairly straightforward idea. New particles should not occupy impossible positions after given the map constraints. For example, particles are not allowed to cross directly through walls. Particle that transition through such obstacles are deleted from the set of particles, as seen in Figure 3.

B. Particle Filter and Map Filtering Implementation for PDR

Particle Filtering for PDR is implemented by incorporating displacement estimates into the particle transition function. For each stride[1], a new particle position x_t^i is generated from the stride length and stride azimuth (heading) estimated from the inertial calculations and is governed by the following transition function:

$$\mathbf{x}_t^i = \begin{bmatrix} x_t^i \\ y_t^i \end{bmatrix} = \begin{bmatrix} x_{t-1}^i + s_t^i cos(\theta_t^i) \\ y_{t-1}^i + s_t^i sin(\theta_t^i) \end{bmatrix} \tag{7}$$

where s_t^i is the stride length of the i-th particle at time t, sampled from normal distribution $N(s_t, \sigma_s)$, with mean stride length s_t and standard deviation σ_s. σ_s is a constant value valid over a wide range of stride lengths. Particle heading θ_t^i is sampled from a normal distribution $N(\theta_t, \sigma_{\theta t})$ with a mean stride heading θ_t and standard deviation $\sigma_{\theta t}$. $\sigma_{\theta t}$ is set to a fixed percentage of the stride-to-stride heading change. The net effect is that in straight segments, the particles remain on their previous course and that during turns, the particles tend to spread out.

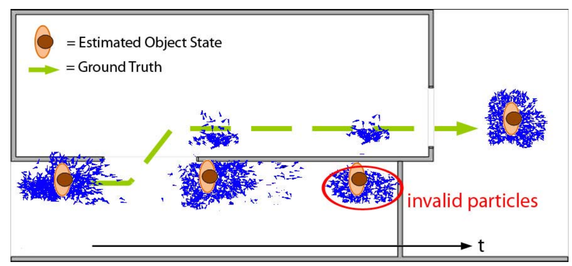
The new particle position, which is determined by the transition function, should not cross walls. If several attempts fail, the particle will be categorized as invalid and the particle weight will also be changed according to the following rule:

$$w_t^i = \begin{cases} 0, & \textit{if new particle crossed a wall} \\ 1/N, & \textit{otherwise} \end{cases} \tag{8}$$

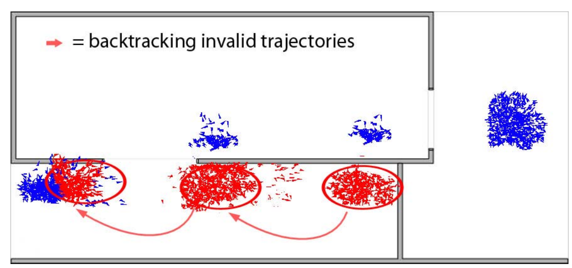
where N is the number of particles.

C. Backtracking Particle Filter

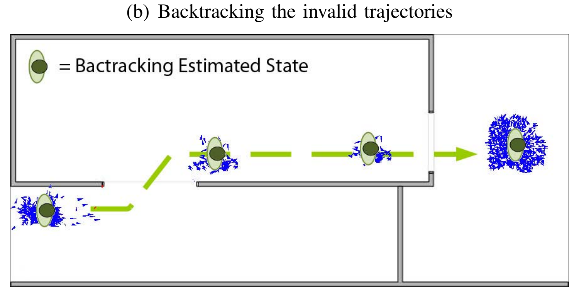
Backtracking Particle Filter is a technique to refine state estimates based on particle trajectory histories. The incorporation of the Map Filtering technique allows the BPF to exploit long-range geometrical constraints. If some particles x_t^i are not valid at some time t, the previous state estimates back to x_{t-k} can be refined by removing the invalid particle trajectories. This is based on assumption that an invalid particle is the result of a particle that follows an invalid trajectory or path. Therefore, recalculation of the previous state estimation $\hat{x}_{t-k}$ without invalid trajectories will produce better estimates. In order to enable backtracking, each particle has to remember its state history or trajectory. The BPF implementation for PDR is illustrated in the following figures.



(a) Detecting invalid particles during PDR with Map Filtering



(b) Backtracking the invalid trajectories



(c) Backtracking estimated states

Fig. 4. BPF with Map Filtering

Figure 4(a) shows a typical phenomenon when a standard Particle Filter is used for Dead Reckoning. It illustrates

[1]Since the motion sensor is on one foot only, the PDR algorithm calculates the distance between footfalls for the same foot. This is the definition of a stride. For adults, one normal stride is between 1.2 and 2.0 m in length.

posterior density of particles in four time steps. The position estimates and the ground truth are shown in the image as well. Map Filtering categorises some particles as invalid at the 3rd step and the invalid particles are not subsequently resampled. Figure 4(b) shows how the Backtracking Particle Filter is used for removing the invalid trajectories. Figure 4(c) illustrates the recalculated state estimates after backtracking. It can be seen that under certain conditions backtracking can improve state estimates relative to a normal PF. The pseudocode below describes the complete BPF algorithm for state refinement.

BACKTRACKING-PF($N, tail$)

1 sampling N particles from initial pdf
2 $tailcount \leftarrow 0$
3 **repeat**
4   get $\mathbf{z}_t$
5   **for** $i \leftarrow 1$ **to** N
6   **do** get $\mathbf{x}_i^t$ from $p(\mathbf{x}_t|\mathbf{x}_{t-1})$
7   calculate $\tilde{w}_t^i = p(\mathbf{z}_t|\mathbf{x}_t^i)$
8   **for** $i \leftarrow 1$ **to** N
9   **do** normalize $w_t^i = \tilde{w}_t^i / \sum_{i=1}^N \tilde{w}_t^i$
10   resample and inherit state history
11   estimate state $\tilde{x}_t = \frac{1}{N}\sum_{i=1}^N \mathbf{x}_t^i$
12   **if** $tailcount \geq tail$
13   **then** $\tilde{\mathbf{x}}_{t-tail} = \frac{1}{N}\sum_{i=1}^N \mathbf{x}_{t-tail}^i$
14   increment $tailcount$
15   increment t
16   **until** $stop$

The main features of the BPF can be seen in steps 6,10, and 13 of the pseudocode. During *prediction sampling* in step 6, a new particle is sampled from the transition pdf $p(x_t|x_{t-1})$ with the Map Filtering technique. In step 10, the resampling step is followed by the inheritance of the state history. This inheritance step will enable the backtracking of invalid trajectories and also the calculation of the backtracking state (step 13).

IV. Tools and Experiments

An XSens MTi motion sensor was solidly attached to one shoe and real inertial data were collected during multiple walks along paths in and out of a small office building. These walks lasted up to 10 minutes each (~ 400 strides), and mimicked reconnaissance missions during a fire. The overall dimensions of the test-bed were approximately 52m x 52m (2704m^2). A tablet PC was used to log raw measurements from the MTi. These were then post-processed with the XSens API and Matlab, generating raw PDR stride length and azimuth tables. Ground truth infomation was generated manually. Both the raw PDR and the ground truth data were then used as input to the PF and BPF applications, both were implemented in C++. Two thousand particles were used during the filtering.

V. Results and Analysis

The PDR displacement and azimuth data were analyzed on their own, with a standard Particle Filter with Map Filtering, and with the BPF technique. Each approach was in turn evaluated with different levels of building plan detail.

The BPF that can take advantage of trajectory histories and long-range (geometrical) constraint information yields excellent positioning performance (1.32 m mean 2D error) with detailed building plan information. More significantly, the BPF using only outlines of external walls yields substantially improved positioning performance (1.89 m mean 2D error) relative to a PDR-only, no map base case (8.04 m mean 2D error). This result is achieved via the elimination of the largest azimuth blunders. Furthermore, the combination PDR measurements and a Particle Filter performs from 3.99 up to 5.17 times better compared to PDR measurements alone. The positioning accuracy is summarized in Table I.

TABLE I
POSITIONING ACCURACY

	PDR	PDR+PF	PDR+BPF
External Wall Map	μ =8.036 σ =8.683	μ =1.892 σ =1.592	μ =1.819 σ =1.498
Escape Map	μ =8.036 σ =8.683	μ =2.012 σ =1.832	μ =1.505 σ =1.094
Detail Map	μ =8.036 σ =8.683	μ =1.553 σ =1.05	μ =1.321 σ =0.821

The analysis of the probability density function (depicted in Figure 5(a), 5(c), 5(e)) show that the estimation errors of the fusion solution follow a Generalized Extreme Value (GEV) distribution. The GEV distribution function is described by:

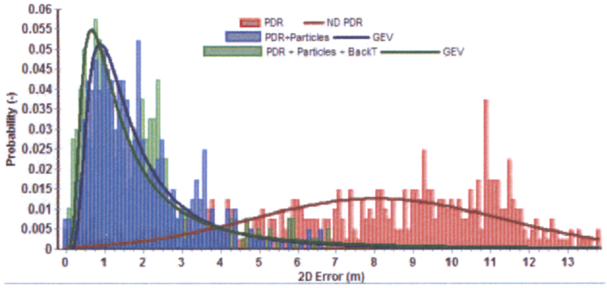
$$F(x, \mu, \sigma, k) = exp\left\{-[1 + k(\frac{x-\mu}{\sigma})]^{-\frac{1}{k}}\right\} \qquad (9)$$

where μ is the location parameter, σ is the scale parameter, and k is the shape parameter. In contrast, the PDR errors are more scattered and the flattened histogram follows a normal distribution. The statistical analysis confirm that the fusion solution is significantly more robust and accurate than the PDR only solution.

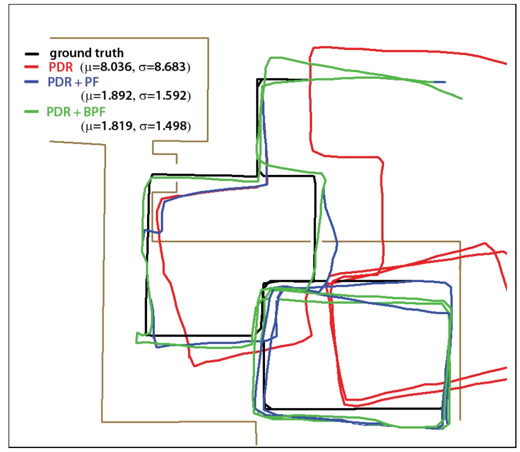
The trajectory evolution over time with external wall map information is shown in Figure 5(b). As expected, the PDR trajectory error grows over time. This can be seen in some part of the trajectory which lie outside the wall boundaries. Figure 5(b) also shows PF+PDR trajectory and BPF+PDR trajectory both using Map Filtering. The trajectories are better since they are constrained by the external wall information.

The sequence of Figure 5(b), 5(d) and 5(f) show how increasing the level of building plan detail can influence the positioning trajectories. Figure 5(d) shows the trajectory with an escape map and Figure 5(f) with a detailed building plan. PDR+BPF performance improves steadily with the level of map detail level (1.82m, 1.5m, and 1.32m 2D mean error). In contrast, PDR+PF performance improves only if the detail level increases significantly (i.e. from external wall map to detail map).

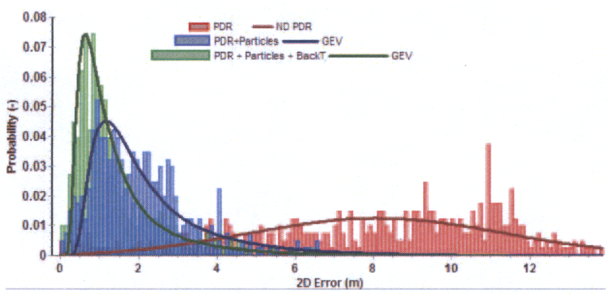
The *tail* value of the BPF is established empirically. The value is optimized by considering several parameters, most



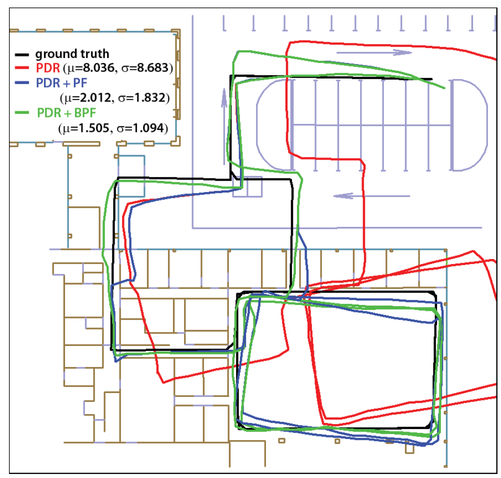
(a) Density functions of error with external wall map



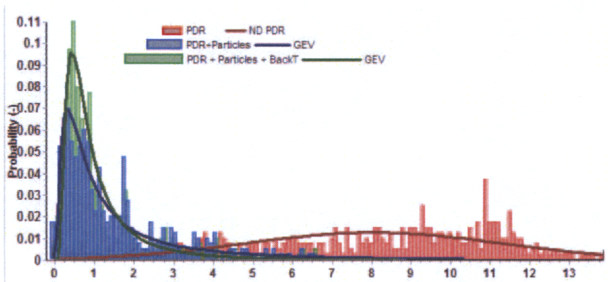
(b) Positioning trajectory with external wall map



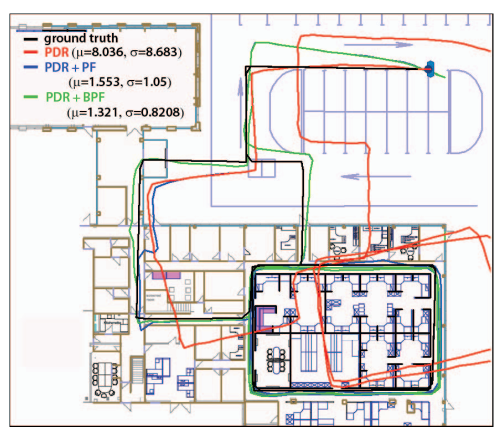
(c) Density functions of error with escape wall map



(d) Positioning trajectory with escape map



(e) Density functions of error with detail wall map



(f) Positioning trajectory with detail wall map

Fig. 5. Positioning results using different building plan details and filter types

notably building plans dimension and trial duration. Figure 6 shows the tail influence on the positioning accuracy when evaluated with the external wall map. Mean positioning error improves up to 50% with the $tail$ values between 40-60 compared with the Particle Filter, meanwhile median positioning error improves 30% with the $tail$ values between 20-40.

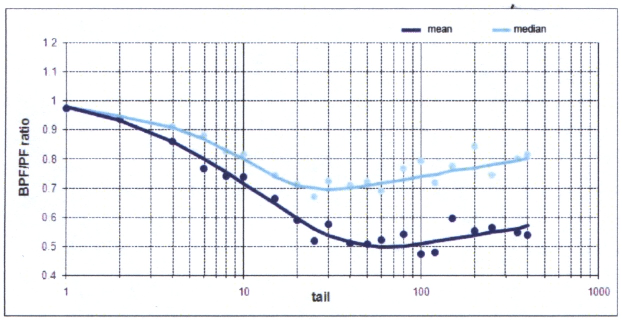


Fig. 6. Influence of tail on the positioning accuracy of BPF with the external wall map

In the future, we plan to implement Expectation-Maximization (EM) clustering technique [11] to determine the $tail$ size.

VI. Conclusion

In this paper a fusion framework for Pedestrian Dead Reckoning and building plans information is described. A novel Backtracking Particle Filter algorithm is also proposed. The fusion framework is evaluated with different levels of building plan detail with the aim of satisfying the positioning requirements of emergency/rescue scenarios.

It has been shown that with a minimum level of map detail, the Backtracking Particle Filter provides a significant performance improvement (1.89 m mean 2D error) relative to a PDR-only, no map base case (8.04 m mean 2D error), and this is only slightly worse than the fully-detailed floor plan case which includes the office cubicle layout (1.55 m mean 2D error). In the minimum plan detail case, largest heading blunders are eliminated via the long-range geometrical constraints exploited by the BPF.

Our results have a substantial practical significance since the estimated level of positioning performance would certainly be useful to first responders. Also, the minimum level of building plan detail required by the approach is probably not difficult to obtain. It could be readily extracted from a cadastral database and even augmented on-the-fly at the emergency scene. It is expected that this performance can be reproduced for many other realistic obstacle layouts and path geometries encountered during emergency incidents. Further experiments will be performed in the future to test this hypothesis.

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