Indoor PDR Performance Enhancement using Minimal Map Information and Particle Filters

Stéphane Beauregard[1], Widyawan[2], Martin Klepal[2]

[1]*Technologie-Zentrum Informatik, Universität Bremen*
28359 Bremen, Germany
bogie@tzi.de
[2]*Center for Adaptive Wireless System, Cork Institute of Technology*
Cork, Ireland
{widyawan, martin.klepal}@cit.ie

***Abstract*—For professional users such as firefighters and other first responders, GNSS positioning technology (GPS, assisted GPS) can satisfy outdoor positioning requirements in many instances. However, there is still a need for high-performance deep indoor positioning for use by these same professional users. This need has already been clearly expressed by various communities of end users in the context of WearIT@Work, an R&D project funded by the European Community's Sixth Framework Program.**

It is known that map matching can help for indoor pedestrian navigation. In most previous research, it was assumed that detailed building plans are available. However, in many emergency / rescue scenarios, only very limited building plan information may be at hand. For example a building outline might be obtained from aerial photographs or cataster databases. Alternatively, an escape plan posted at the entrances to many building would yield only approximate exit door and stairwell locations as well as hallway and room orientation. What is not known is how much map information is really required for a USAR mission and how much each level of map detail might help to improve positioning accuracy. Obviously, the geometry of the building and the course through will be factors consider.

The purpose of this paper is to show how a previously published Backtracking Particle Filter (BPF) can be combined with different levels of building plan detail to improve PDR performance. A new in/out scenario that might be typical of a reconnaissance mission during a fire in a two-story office building was evaluated. Using only external wall information, the new scenario yields positioning performance (2.56 m mean 2D error) that is greatly superior to the PDR-only, no map base case (7.74 m mean 2D error). This result has a substantial practical significance since this level of building plan detail could be quickly and easily generated in many emergency instances. The technique could be used to mitigate heading errors that result from exposing the IMU to extreme operating conditions. It is hoped that this mitigating effect will also occur for more irregular paths and in larger traversed spaces such as parking garages and warehouses.

***Index Terms*—Indoor Posititioning, Pedestrian Dead Reckoning, Map Filtering, Particle Filters**

I. Introduction

For professional users such as firefighters and other first responders, GNSS positioning technology (GPS, assisted GPS, Galileo) can satisfy outdoor positioning requirements in many instances. However, high-performance deep indoor positioning for use by these same professional users [1] has yet to be demonstrated. The need has been clearly expressed by various end user communities in the context of WearIT@Work, an R&D projects funded by the European Community's Sixth Framework Program.

The results of a recent "location trial" show that pedestrian-oriented inertial technology achieves interesting performance (stand-alone positioning accuracy better than 3 meters RMS after 4 minutes and less than 6 meters RMS after 8 minutes of continuous pedestrian walk), but still lacks robustness against specific environmental conditions (in particular magnetic disturbances affecting orientation estimation) and users' walking behaviour [2]. There will undoubtedly be advances in MEMS sensors and the associated estimation/compensation algorithms that will allow for greatly improved positioning performance. However, it may be argued that real USAR scenarios will be remain technically very challenging, due to temperature variations and completely unconstrained locomotion patterns.

It is known that map matching can be used to improve the performance of indoor pedestrian navigation systems [3]. In most previous research using this approach, it was assumed that detailed building plans are available. These were used unmodified or reduced to a node and edge representation and then combined with particle filters. However, in many emergency / rescue scenarios, only very limited building plan information may be available. For example, a building outline could be obtained from aerial photographs or cataster databases. Alternatively, an escape plan posted at the entrances to many building could yield approximate exit door and stairwell locations as well as hallway and room orientation. What is not known is how much map information is really required for a USAR mission and how much each level of map detail might help to positioning accuracy.

In a previous publication [4], the authors described a framework for fusing building plans and PDR motion measurements. A novel implementation of Map Filtering (MF), called the Backtracking Particle Filter (BPF), was evaluated with real PDR displacement data and a building plan as input. It was shown that the BPF can take advantage of long-range (geometrical) constraint information provided by various levels

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

of building plan detail. It was clear from that study that the geometry of the building and the course through it would have an affect performance. In this paper, we extend our earlier results by evaluating the approach on an additional in/out scenario that is representative of a reconnaissance mission through a two-story office building. We also incorporate an indoor/outdoor binary measurement that prevents particle cloud divergence.

The remainder of the paper is organized as follow. In Section II, a PDR based positioning system is briefly introduced. Particular attention is paid to the PDR displacement error mechanisms. The Map Filtering approach and the Backtracking Particle Filter are reviewed in 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 with an outlook on future experiments.

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 attached to, or mounted in, footwear (Figure 1). Kalman Filtering (KF) and strap-down mechanization equations can be applied to the raw IMU measurements for estimating foot displacements. Very briefly, a rotation matrix that brings the body (i.e. sensor) coordinate frame to the local/level coordinate frame is estimated. Then the accelerations in the body frame are rotated to the local/level frame with this matrix and the resulting accelerations are double integrated to yield a displacement in the local/level frame. Zero-velocity updates (ZUPs) are performed when the accelerations and rate gyro measurements drop below empirically determined thresholds. During short outdoor segments where GPS position fixes are available, sensor biases can be estimated and a coarse initial alignment can be performed. This approach is similar to that taken in [5][6][7] and elsewhere. Note that it contrasts with the one described in e.g. [8] where step lengths and directions are estimated indirectly by acceleration and compass measurements taken at some solid anchor point on the body (e.g. hip, torso) and by exploiting user-dependent step frequency to step length relationships.

It is usually possible during even short ZUPs at footfalls to estimate the gravity vector from accelerometer readings and thereby determine roll and pitch angles. These facts can be exploited by the KF to correct for gyro drifts around these two axes. Gyro drift around the yaw axis is typically controlled via 3D magnetometer readings. Unfortunately, in indoor environments, magnetic disturbances can make magnetometer-based orientation estimates very problematic. Consequently, more weight has to be (adaptively) given to the yaw gyro measurement than to the magnetometers. The consequence can be a slowly drifting heading.

We are in the process of writing our own adaptive quaternion/Kalman sensor fusion filter (as was done in [5]) for estimating the rotation matrix, sensor biases or covariances. However, for the experiments presented here, we used the XSens MTi sensor's software API to get the rotation matrix and compensated accelerometer readings. Note that the XSens filter is designed for limb motion capture. It was not designed to handle the high dynamics at the foot and it cannot directly exploit ZUP information. When using the output from this software in the mechanization algorithm described above, the heading of the estimated path does not show the smooth drift pattern typical of dead reckoning systems. Rather, we have observed over many experiments that there are sudden yaw/heading jumps when we stop moving for a few seconds and/or when we pass through an area with a high density of magnetic disturbances. In addition, on-the-spot turns often produce greatly under- or overestimated heading/yaw changes. It would appear that at these moments, the adaptive filter is modifying the magnetometer/gyro relative weighting and correcting for accumulated orientation errors due to gyro noise and bias drift. The net effect is that when the azimuth (heading) change between strides is small, we can assume that a jump artifact did not occur and can put a high confidence on the estimated heading. In other words, straight segments are mostly correct. On the other hand, when a large heading change is measured, it may be due to a jump artifact or a real turn. We therefore put less confidence on measured turns. These observations were incorporated into the particle transition function described in the next section.

In our own filter implementation, we will very likely get a different (and hopefully smaller) heading error behaviour than the one described here. However, regardless of the sophistication of the filter or the quality of the sensors, the extreme operating conditions of USAR missions (high temperatures, in particular) will perturb IMU sensors. MEMS gyros are quite sensitve to temperature changes and may also exhibit non-linearities that cannot be easily modeled. We argue here that significant heading errors will likely still occur when this type of PDR system is deployed in the real world. Fortunately, these heading errors can be effectively mitigated with the techniques described in the sequel.

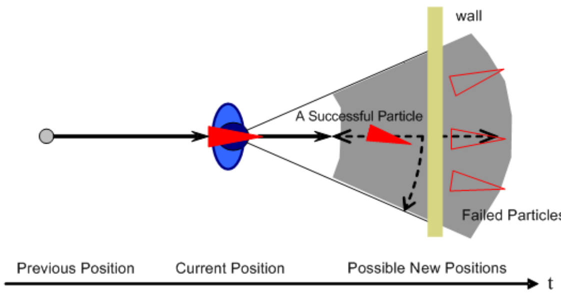


Fig. 2. Particle Transition Near Obstacles: If a particle tries to move to an impossible location, e.g. across walls defined in the map, it will be killed off.

III. Particle and Map Filtering

Particle Filtering is a technique that implements a recursive Bayesian filter using the Sequential Monte-Carlo method [9][10]. It is particularly good for dealing with non-linear and non-Gaussian estimation problems [11]. 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 [10]:

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

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.

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 [12]. Map Filtering implements a fairly straightforward idea. New particles should not occupy impossible positions 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 or downweighted, as depicted in Figure 2.

A. 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:

$$\mathbf{x}_t^i = \begin{bmatrix} x_t^i \\ y_t^i \end{bmatrix} = \begin{bmatrix} x_{t-1}^i + s_t^i cos(\theta_t^i) \\ y_{t-1}^i + s_t^i sin(\theta_t^i) \end{bmatrix} \tag{2}$$

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. s_t is set to the inertially-calculated stride length estimate and σ_s is set to a fixed value around 5% of an average stride length or about 10 cm. The 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 (10%) of the inertially-calculated 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 particle cloud tends to spread out. The particle cloud also tends to spread out along the down-track direction.

The new particle position, which is determined by the transition function, should not be an impossible one. For example, movement across walls should not occur. If a particle attempts to cross such an obstacle, the particle weight is changed according to the following rule:

$$w_t^i = \begin{cases} 0, & \textit{if new particle moves to impossible location} \\ 1/N, & \textit{otherwise} \end{cases} \tag{3}$$

where N is the number of particles. For the first few failed attempts, the particle is downweighted and returned to its original position. After these few attempts, the particle is removed from the particle set.

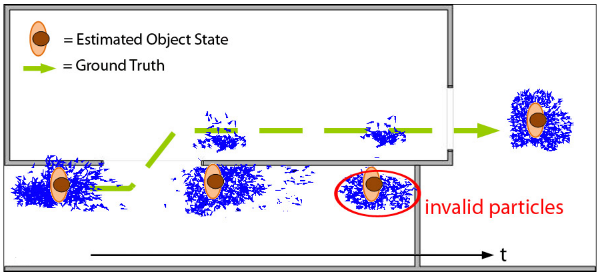
In addition to a basic wall-crossing rule, we also implemented a more global rule with respect to the building perimeter. The idea is that GPS availability can provide a quite strong indications whether one is indoors or outdoors. The C/No values, number of tracked satellites, lock state or similar measurements can be used to synthesise an indoor/outdoor indicator. Particles that are on the inside of the building when GPS signals are still available are penalized. Those that are outside when GPS signals are not available are also penalized. The net effect of this rule is that it prevents the particle cloud from breaking up into isolated clusters inside and outside the buiding and that diverge away from each other.

B. Backtracking Particle Filter

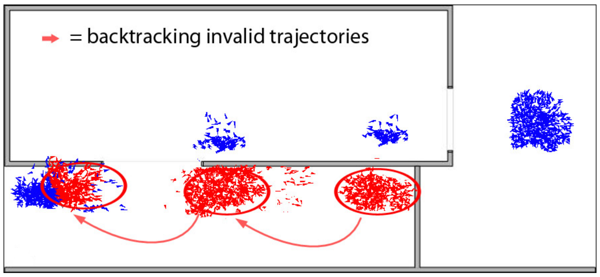
The Backtracking Particle Filter (BPF) is a technique for refining state estimates based on particle trajectory histories. The incorporation of the Map Filtering technique allows the BPF to exploit long-range geometrical constraints. If some particles x_t^i are not valid at some time t, the previous 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.

Figure 3(a) shows a typical phenomenon when a standard Particle Filter is used for Dead Reckoning. It illustrates 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 3(b) shows how the Backtracking Particle Filter is used

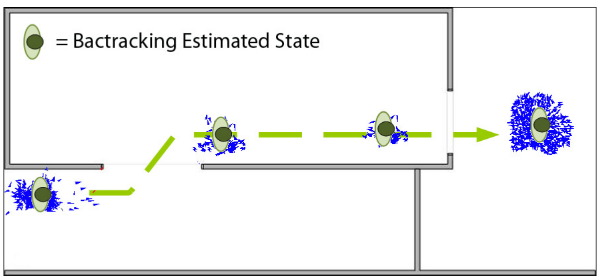
[1]Since the motion sensor is on one foot only, the PDR algorithm calculates the distance between footfalls for the same foot. This is the definition of a stride. For adults, one normal stride is between 1.2 and 2.0 m in length.



(a) Detecting invalid particles during PDR with Map Filtering



(b) Backtracking the invalid trajectories



(c) Backtracking estimated states

Fig. 3. BPF with Map Filtering

for removing the invalid trajectories. Figure 3(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.

IV. Tools and Experiments

An XSens MTi motion sensor was solidly attached to one shoe and inertial data were collected during a walk along a path in and out of a multi-storey office building. This walk lasted around 10 minutes ($\sim$ 330 strides), and mimicked a reconnaissance mission during a fire. The overall dimensions of the test-bed were approximately 60m x 60m in an L-shaped building wing. The path included a straight, ground-level outdoor segment plus two flights of staircases to the first floor.

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 based on surveyed reference points. A synthetic, binary GPS availability flag was generated manuallly based on the ground truth path. The stride length and direction, availibility flag and ground truth data were then used as input to the MF application, implemented in C++. Two thousand particles were used during the filtering.

Note that it is possible to obtain quite accurate height change information using the foot-inertial technique [2] and to do position estimation and map filtering in 3D. In these experiments however, only 2D maps were used. Some walls on adjacent floors were removed to allow freer particle movements in certain locations, for example up winding stairwells.

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 filter approach was in turn evaluated with two different levels of building plan detail.

The basic PDR trajectory which does not take advantage of any geometrical information is shown in red in Figure 4. As expected, the PDR trajectory error grows over time. This can be easily seen as some part of the trajectory already lie outside the wall boundaries before the end of the experiment. A number of heading/azimuth jumps are also apparent. Figure 5(a) and 5(b) shows PF+PDR trajectory and BPF+PDR trajectories respectively both using Map Filtering. These trajectories are far better than the PDR one since they are constrained by the building plan information.

The positioning accuracies for this experiment are summarized in Table I. The BPF which takes advantage of trajectory histories and long-range (geometrical) constraint information yields excellent positioning performance (0.74 m mean 2D error) with detailed building plan information. More significantly, the BPF using only outlines of external walls yields substantially improved positioning performance (2.56 m mean 2D error) relative to a PDR-only, no map base case (7.74 m mean 2D error). This result is achieved via the elimination of the largest azimuth blunders. It is clear that increasing the level of building plan detail positively influences the quality of the positioning.

TABLE I
Positioning Error

	PDR	**PDR+PF**	**PDR+BPF**
External Wall Map	μ =7.738 σ =8.741	μ =3.103 σ =2.939	μ =2.557 σ =2.606
Detail Wall Map	μ =7.738 σ =8.741	μ =1.083 σ =0.8431	μ =0.7432 σ =0.6046

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

$$F(x,\mu,\sigma,k) = exp\left\{-[1+k(\frac{x-\mu}{\sigma})]^{-\frac{1}{k}}\right\} \qquad (4)$$

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.

VI. Conclusion

In this paper, a previously-described framework for fusing Pedestrian Dead Reckoning and building plans information was evaluated with different levels of building plan detail. It has been shown that with a minimum level of map detail, the Backtracking Particle Filter provides a significant performance improvement (2.56 m mean 2D error) relative to a PDR-only, no map base case (7.74 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. These results confirm those given in [4].

We are in the process of writing our own adaptive quaternion/Kalman sensor fusion filter (as done in [5]) for estimating the rotation matrix, sensor biases and covariances. We will very likely get a different (and hopefully smaller) heading error behaviour than the one described here. That said, there will always remain a certain amount of heading error due to operating conditions that are hostile to MEMS sensors. As shown, these heading errors can be effectively mitigated with building map information.

Our results have a substantial practical significance since the estimated level of positioning performance would certainly be useful in emergency/rescue scenarios. Also, the minimum level of building plan detail required by the approach is probably not difficult to obtain. Future experiments will determine if the approach has any value for more erratic paths and for paths through larger spaces such as parking garages or warehouses.

Acknowledgment

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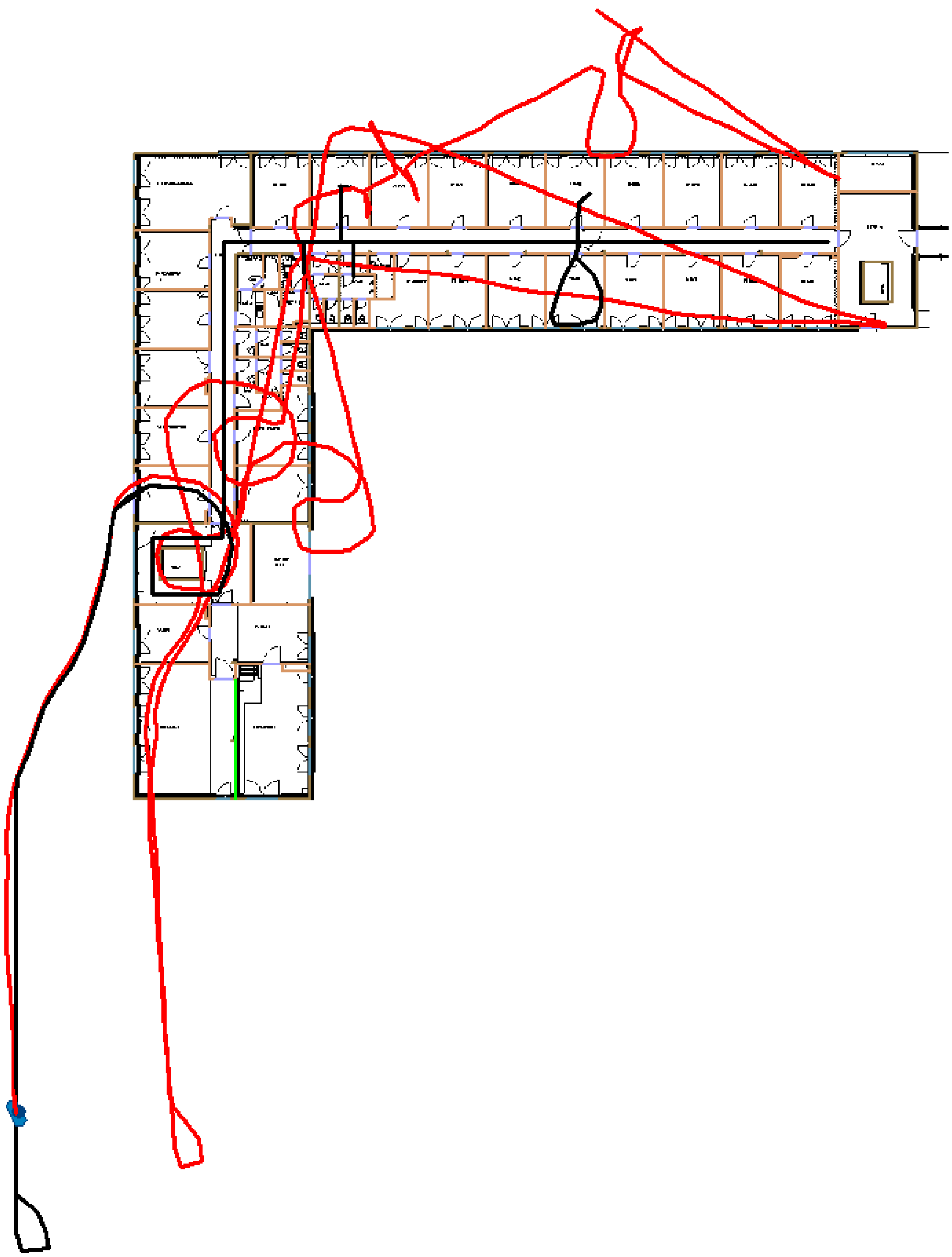
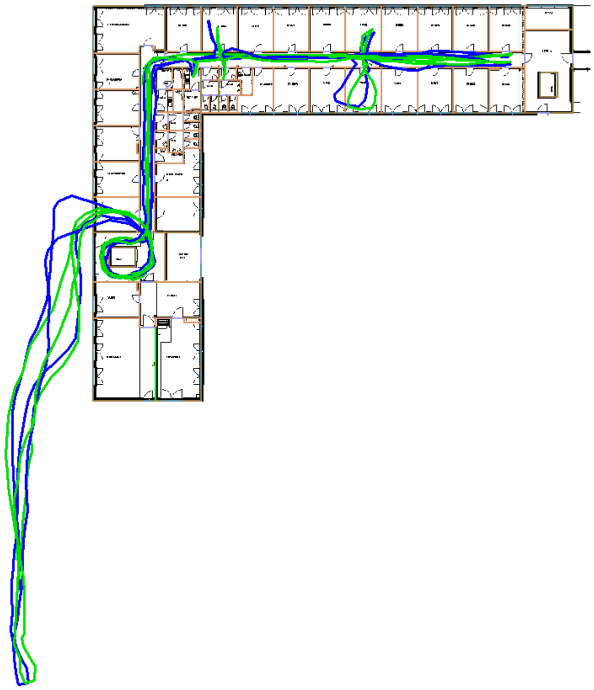
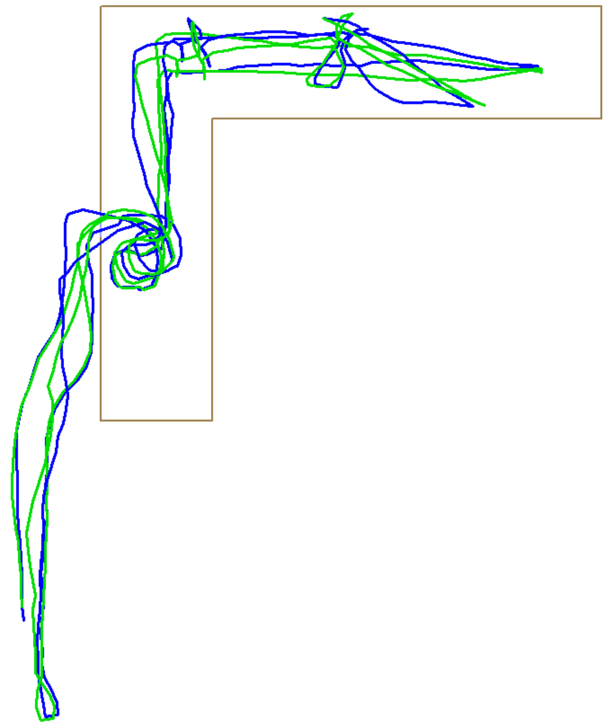


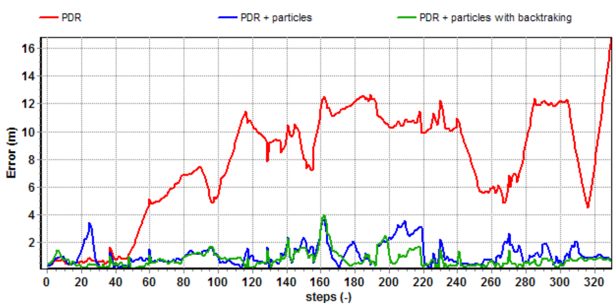
Fig. 4. Building Floor Plan, Ground Truth (black line) and PDR Path (red line). The blue shape on the lower left is standing at the start position.



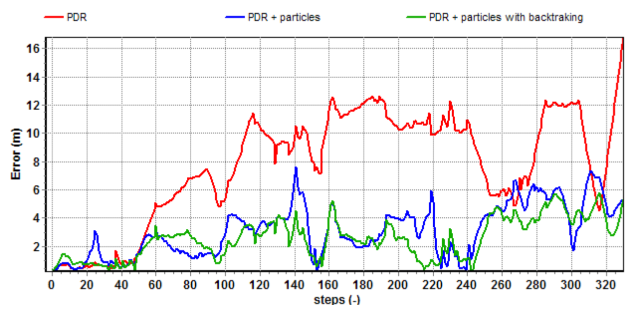
(a) Estimated trajectories with detail wall map



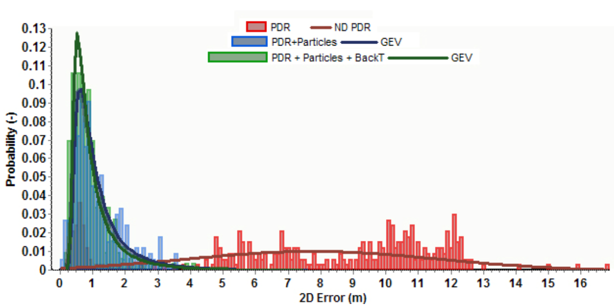
(b) Estimated trajectories with external wall map



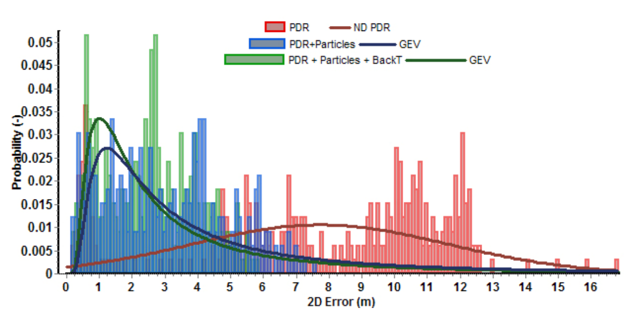
(c) Position error vs steps with detail wall map



(d) Position error vs steps with external wall map



(e) Position error PDFs with detail wall map



(f) Position Error PDFs with external wall map

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