Pedestrian Inertial Navigation with Building Floor Plans for Indoor Environments via Non-recursive Bayesian Filtering

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Abstract— **In this paper, we present a pedestrian navigation method for indoor environments that uses a novel non-recursive Bayesian filter. Developed method takes building floor plans into account to compensate for error-prone heading measurements provided by a foot mounted micro electro-mechanical system (MEMS) inertial measurement unit (IMU). Zero velocity updates (ZUPT) are implemented intuitively to estimate sensor bias/drifts and subsequently dead reckoning (DR) equations calculate the pedestrian location from corrected velocity. Despite high accuracy in estimating traveled distance, navigation solution is unacceptable due to incorrect heading estimates. Methods to fix the heading estimation problem typically exploit particle filter (PF) framework. Limited computational power of IMU board, however, cannot afford a PF implementation therefore a novel approach alternative to recursive Bayesian filtering (RBF) is developed. Proposed filter uses the static floor plan density distribution and an extended motion model to eliminate heading errors in pedestrian location estimation.**

Keywords— MEMS IMU; pedestrian navigation; ZUPT; dead reckoning; recursive Bayesian filtering; floor plan; map matching

I. INTRODUCTION

There is significant demand for pedestrian navigation system (PNS) in many applications. Global positioning system (GPS) is the main choice for navigation. It provides long term and absolute position information when required conditions are met. However, it suffers from street canyon effect, multipath effects, and blockages. Furthermore, it becomes totally unavailable due to attenuation for indoors. Alternative absolute PNS can be built by installing beacons in the environment. A network of receivers or emitters are placed at known locations, and the position is estimated by triangulation. They are termed local positioning systems (LPS). There are applications using WiFi, UWB, RFID, WLAN, ultrasound or computer vision in LPS [1]. Another popular method is fingerprinting [2]. Despite promising a high accuracy solution, high labor input required to complete offline process and infrastructure costs avoid common use of fingerprinting. A common problem that occurs both outdoors and indoors is, many times the absolute positioning system signals are degraded or totally blocked and need for a complementary navigation system rises. The most preferred technology is inertial sensors in this case. In the extreme case, they may not be an absolute positioning system for periodic corrections and the navigation solution could be totally dependent on inertial sensors. In this case, the navigation system is a self-contained system.

Quality of the inertial sensors are the dominant factor in inertial navigation system performance. The recent advances in technology yielded cheap and small size MEMS sensors. However, drift rates for both accelerometers and gyroscopes in a MEMS IMU are several orders of magnitude higher than in high-grade aviation IMU. The solution is to model, estimate and eliminate drifts in MEMS sensors. MEMS accelerometers and gyroscopes are subject to slow changing bias and random noise [3]. Many researchers formulated a 15-state extended Kalman filter (EKF) to estimate sensor bias/drifts, orientation, velocity and position [4,5]. Foot is selected for IMU location for periodic correction of velocities so-called ZUPT. The main focus is to detect the stationary period of IMU to accurately estimate drift. Eventually, in every step, velocity is corrected, and hence the cumulative errors in distance traveled are avoided. Despite the success in stride length estimation, ZUPT fails to observe heading errors [4]. To correct for heading, magnetometer aid and heuristic drift reduction [3,5] methods are used. Moreover, heuristic drift elimination methods exploit dominant directions of maps while traversing streets or man-made structures (i.e., map-matching) in continuation of drift reduction studies. The topological map matching approach for indoor applications uses a link-node representation of a building plan [6]. Restricting the navigation path to node connecting edges is generally impractical especially in large open halls. In these cases, probabilistic approaches provide reliable solution to the map-matching problem. PF based map-matching methods simulate pedestrian location under nonlinear motion and measurement models and non-Gaussian uncertainties by taking building maps into account [7,8]. Despite its robustness, the need for many particles in approximating related nonparametric distributions cause PF to be computationally high cost and consequently restrain the method when there is limited computational power. This study approaches PNS for indoors in a stochastic way like PF methods. However to eliminate the need for high computational cost, it formulates the RBF scheme distinctively. Floor plan information is employed in a novel way. Opposing to other studies, no gyro bias is modeled

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therefore highly unreliable heading measurements from IMU are observed.

II. METHODOLOGY

A. Zero-Velocity Updates

Due to employment of the built-in AHRS algorithm to estimate orientation, an intuitive implementation of ZUPT is used [9]. Main idea is to detect the pedestrian steps and stationary phase of the gait accurately and then estimate sensor bias and errors periodically. In this study, accelerometers and gyro rates are filtered and thresholded to determine the steps and the stationary period durations [5]. Subsequently the estimated errors are subtracted from the velocity for compensation. In this way ZUPT algorithm fixes the errors in stride lengths and eventually the IMU accurately reconstructs total traveled distance. On the other hand, gyro bias and motion direction estimate cannot be observed by ZUPT [4] therefore the main challenge remains the estimation of heading angle in pedestrian navigation.

B. Recursive Bayesian Filtering (RBF)

Position of the pedestrian is the hidden state $\mathbf{x_k} \in \mathbb{R}^n$ and the noisy measurements are $\mathbf{z_k} \in \mathbb{R}^m$ where subscript k denotes time index. A first order Markov model is used for the estimation of pedestrian location [7]. The entire history of hidden states is denoted by X_k and measurements are denoted by Z_k. The general estimation problem can be described by

$$\mathbf{x_k}=\mathbf{f}(\mathbf{x_{k-1}})+\mathbf{w_{k-1}} \quad (1)$$

$$\mathbf{z_k}=\mathbf{h}(\mathbf{x_k})+\mathbf{v_k} \quad (2)$$

where $\mathbf{w} \in \mathbb{R}^n$ stands for process noise and $\mathbf{v} \in \mathbb{R}^m$ stands for the measurement noise, both statistically independent. Functions $\mathbf{f}$ and $\mathbf{h}$ are nonlinear functions. Equation (1) describes the motion of the pedestrian and called the prediction step (i.e., time update), and (2) independent observations and called the correction step (measurement update). In this stochastic model, the goal is to estimate it $\mathbf{x_k}$ with aid of independent observations $\mathbf{z_k}$. Posterior distribution is obtained after applying both steps as follows

$$p(\mathbf{x_k}|Z_k)=\frac{p(\mathbf{z_k}|\mathbf{x_k})p(\mathbf{x_k}|Z_{k-1})}{p(\mathbf{z_k}|Z_{k-1})} \quad (3)$$

where the denominator serves as a normalizing constant. The term $p(\mathbf{z_k}|\ \mathbf{x_k})$ is the sensor likelihood and $p(\mathbf{x_k}|Z_{k-1})$ the prior distribution acquired after applying the motion model given in Equation (1). In cases where $\mathbf{f}$ and $\mathbf{h}$ are linear and noises $\mathbf{w}$ and $\mathbf{v}$ are normally distributed, analytical solution is available in the form of Kalman filter. Closed-form solution of the posterior distribution is difficult to find most of the time therefore suboptimal solutions are derived in the form of EKF, unscented KF, and most general case PF [11]. The computational cost increases as linearity and Gaussianity assumptions are violated more and more. In this work, we seek a solution that can deal with nonlinearities on the floor map due to walls while eliminating the need for a high cost suboptimal solution such as PF.

C. Proposed Method

Unlike PF based map-matching navigation studies [7,8], floor plan is exploited by building a rasterized probability distribution function (pdf), $p(\mathbf{x_k}|FP)$, that remains static. Density levels are proportional to walking likelihood of the pedestrian in the corresponding locations as shown in Fig. 1.

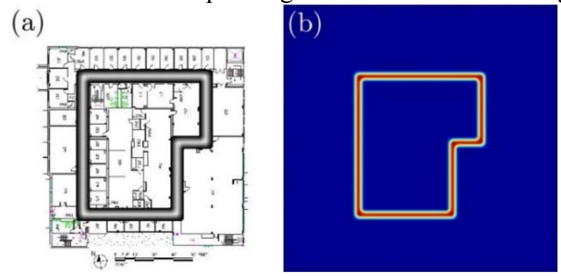

Fig. 1. Static floor plan pdf $p(\mathbf{x_k}|FP)$. (a) Gray-scale color map for the hallways. (b) Overall pdf with standard colormap.

Sensor likelihood is expressed as follows

$$\mathbf{z_k}=\begin{pmatrix} z_k^N \\ z_k^E \end{pmatrix}=\hat{\mathbf{x}}_{\mathbf{k-1}}+d_k\begin{pmatrix} \sin(\hat{\psi}_{k-1}+\delta\psi_k) \\ \cos(\hat{\psi}_{k-1}+\delta\psi_k) \end{pmatrix} \quad (4)$$

where z_k^N and z_k^E are pedestrian coordinates according to IMU in north and east directions, $\hat{\mathbf{x}}_{\mathbf{k-1}}$ is the previous estimate, d_k is the stride length and $\delta\psi_k$ is the heading change estimates, respectively, and $\hat{\psi}_{k-1}$ denotes the heading estimate at previous step. In this study, a simple calibration process is followed disregarding sophisticated gyro error models therefore $\delta\psi_k$ is not as reliable as d_k. However, both terms indirectly affect pedestrian location likelihood as given in Equation (4). For this reason, there is considerable uncertainty in likelihood term, and this problem is solved with aid of aforementioned static floor plan pdf and extended motion model. The extended motion model $p(\mathbf{x_k}|\mathbf{x_{k-1}}, \ldots, \mathbf{x_{k-n}})$ predicts locations on a line when the pedestrian is moving in straight segments, and on a curve when close to corners in the hallways. Number of previous estimates used n is a design parameter. The means of sensor likelihood and prior pdfs are located on a pedestrian encircling pdf $p(\mathbf{x_k}|d_k, \mathbf{x_{k-1}})$ that represents location density according to IMU provided stride length. Notice that a 1d Gaussian is formed if a line is drawn from the pedestrian to any direction for the circular distribution. The fact that ZUPT updates give accurate stride length estimates is exploited to construct this pdf. All described individual distributions are illustrated in Fig. 2. The product of individual terms form the final nonparametric posterior distribution.

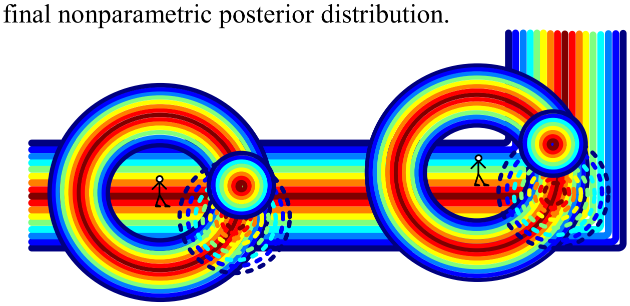

Fig. 2. Combination of individual distributions (i.e., prior, likelihood, only stride length based likelihood and static floor plan) that forms posterior pdf.

As the closed-form solution of the nonparametric posterior pdf is intractable, the final filtering equation for the non-recursive Bayesian filter is given as

$$p(\mathbf{x_k}|Z_k) \propto p(\mathbf{x_k}|FP)p(\mathbf{x_k}|d_k,\mathbf{x_{k-1}}) \\ p(\mathbf{z_k}|\mathbf{x_k})p(\mathbf{x_k}|\mathbf{x_{k-1}},\ldots)p(\mathbf{x_{k-1}}|Z_{k-1}) \quad (5)$$

and via a mode-seeking algorithm, required inference can be made.

III. EXPERIMENTAL SETUP AND RESULTS

The 9-dof Razor IMU [10] employed in the experiments can be seen in Fig. 3. It consists of orthogonal 3-axis gyroscopes, accelerometers, and magnetometers. All data is processed in the on-board microcontroller with 8Mhz clock speed. The limited computational power compels derivation of much more efficient estimation algorithms other than PF based map-matching approaches. A wireless transmitter XBee is used to send data to host computer which receives transmitted data with another XBee but with a receiver configuration. All programming interface is C++, both on microcontroller and host computer.

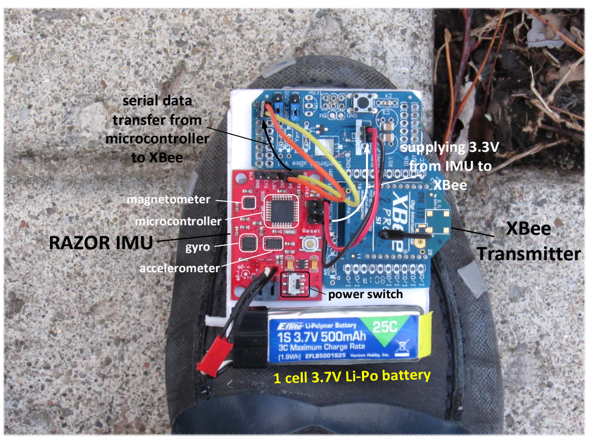

Fig. 3. Razor IMU used in the experiments.

Two experiments are conducted for indoor environments and corresponding results are shown in Fig. 4 and Fig. 5, respectively. Covariance of sensor likelihood and prior densities in Equation (5) are set to high values (i.e., close to uniform distribution) in these traverses which leaves static map density term as the dominant factor in the filter. Both experiments yield successful navigation solutions with disclosure error less than %1. Calibration of prior and likelihood density parameters is a future goal for more complicated maps and repetitive results.

IV. CONCLUSIONS

This work develops an alternative method for a PF based map-matching algorithm which requires to employ distributed or more powerful computational platforms for indoor PNS. A novel usage of floor plan information along with an extended motion model helps compensating for error-prone motion direction of pedestrian while enabling real-time performance with limited computational power. Future goals include traverses on various maps and repeatability.

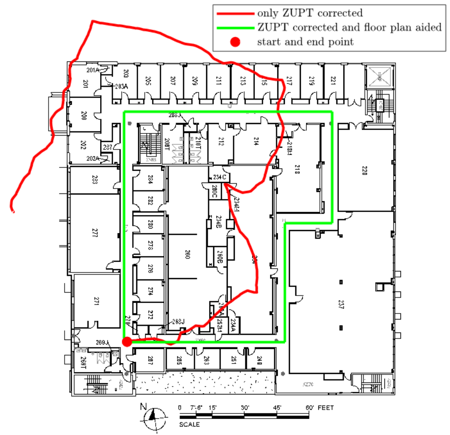

Fig. 4. Experimental navigation results for the first building.

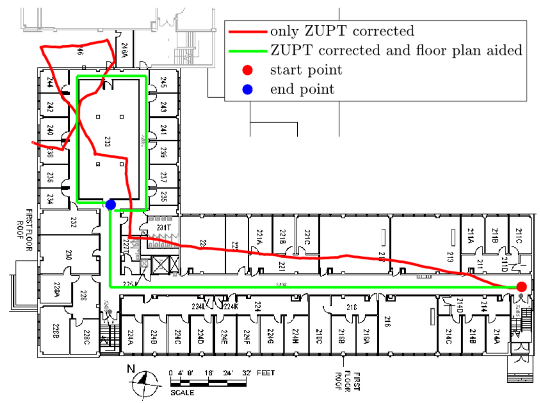

Fig. 5. Experimental navigation results for the second building.

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