Strap-Down Pedestrian Dead-Reckoning System

Pragun Goyal, Vinay J. Ribeiro, Huzur Saran, and Anshul Kumar
Department of Computer Science and Engineering, Indian Institute of Technology, Delhi.
Email: pragun.goyal@gmail.com,{vinay,saran,anshul}@cse.iitd.ac.in

***Abstract*—This paper presents a waist-worn Pedestrian Dead Reckoning (PDR) System that requires minimal end-user calibration. The PDR system is based on an Inertial Measurement Unit (IMU) comprising of a tri-axial accelerometer, a tri-axial magnetometer and a tri-axial gyroscope. We propose a novel heading estimation scheme which uses a Quaternion-based Extended Kalman Filter that reduces magnetic disturbances and corrects for them. With the help of accelerometer measurements, we detect steps events and estimate step lengths. Experimental results show that our algorithms provide a relative distance error of about 5% in indoor environments.**

***Index Terms*—Inertial navigation, Dead reckoning**

I. INTRODUCTION

Indoor environments, street canyons and areas with heavy tree cover are typical examples of places where the GPS fails to perform satisfactorily due to degradation of satellite signals. A popular solution to this problem in the context of Pedestrian Navigation Systems (PNS) is to integrate the GPS with an Inertial Measurement Unit (IMU) [1]. Typically, IMU-based Pedestrian Dead Reckoning (PDR) systems model the motion of human body during various activities to overcome the large drift introduced by the numerical integration of IMU measurements [2], [3].

We present a waist-worn IMU based PDRS that requires minimal user-specific calibration. The IMU contains a tri-axial gyroscope, a tri-axial magnetometer and a tri-axial accelerometer. A waist-worn IMU is more practical for consumer navigation purposes than a shoe-mounted one which requires an IMU to be attached to the shoe [4]–[9]. However, waist-worn systems need more sophisticated algorithms for navigation than shoe-mounted ones because the pelvis is never stationary during walking motion, unlike the foot which is stationary during the stance phase. The techniques described in this paper can be extended to placement of the IMU on those parts of body that move with the pelvis. This includes the case where the device in carried in a trouser pocket [10].

We propose the use of a Quaternion based Extended Kalman Filter (EKF) to estimate the full 3D attitude of the sensor module. Simple numerical integration of the gyroscope data introduces drift errors and is insufficient for heading estimation. Some of these errors can be reduced by combining the gyroscope data with magnetometer data. However, magnetic disturbances introduce errors in the heading obtained from magnetometers. Our method allows estimation of the magnetic disturbance thereby increasing estimation accuracy.

We use the method described by Wienberg et al. to perform step length estimation [11]. This method is known to perform well even if generalized calibration values are used for different users [10]. Other approaches use various kinetic models to estimate the step length using accelerometer measurements [11]–[14]. These models, however, require that some parameters be tuned for each different user. Although user specific calibration typically results in more accurate estimation of step length, acquiring data for calibration is quite challenging. This is especially true for kinetic models that are sensitive to external factors like hardness of floor, footwear, etc.

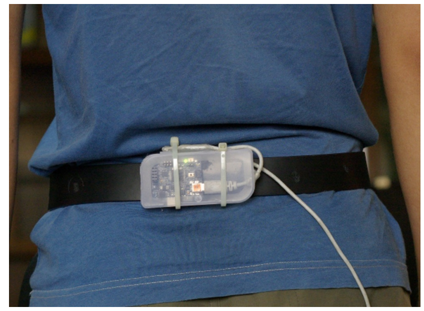

Fig. 1. Sensor module worn by a user

II. HEADING ESTIMATION

Gyroscopes and magnetometers are popularly used in dead reckoning systems to estimate the heading. Gyroscope measurements contain bias and scale errors which introduce a drift in the heading estimate. A well calibrated compass, on the other hand, is known to give a stable heading. However, external magnetic disturbance due by electronic systems, power lines, magnetic objects like speakers, motors are known to degrade the performance of a compass. This is especially true for indoor environments.

Our method uses an Extended Kalman Filter to estimate the full 3D attitude of the IMU using the data from the gyroscope, the magnetometer and the accelerometer. Gusenbauer et al. have described a method that applies a simple linear recursive filter on the magnetometer measurements [15]. This method uses a filter weight parameter that can take different values for different users. As a three-axis gyroscope is fast becoming a standard feature in smartphones and Personal Digital Assistant (PDA) devices, more sophisticated techniques can be used to counter the errors introduced by indoor magnetic disturbance. Moreover, as the rotation of IMU is not constrained to the vertical axis, a full 3D attitude estimation can possibly achieve better heading accuracy by incorporating gyroscope measurements for three orthogonal axes. Owing to several computational benefits offered by Quaternions over other attitude representations including Euler angles and Direction Cosine Matrix (DCM) [16], we chose to represent the full 3D attitude as a quaternion.

Several other techniques have been devised to handle the errors introduced by magnetic disturbances. A Complementary Filter that models the errors introduced by magnetic disturbance is described by Roetenberg et al. [17]. Sabatini et al. have described a quaternion based EKF in which, the magnetic disturbance is estimated as magnetometer bias error in the state vector [18]. This treatment of magnetic disturbance is equivalent to estimation of a magnetic disturbance vector fixed in the reference frame of the sensor system. However, as the magnetic disturbance is a property of a particular location, we estimate the magnetic disturbance in a reference frame fixed with respect to ground.

A magnetometer measures the total magnetic field ($\vec{H}$) at a point, which is given by,

$$\vec{H} = \vec{H_{earth}} + \vec{H_{ext}} \tag{1}$$

where $\vec{H_{earth}}$ and $\vec{H_{ext}}$ denote the Earth's magnetic field at the point and the external magnetic field respectively.

$\vec{H_{ext}}$ can be split into two components, $\vec{d}$ and $\vec{H_{system}}$, where $\vec{H_{system}}$ is the constant magnetic field generated by the navigation system (including the user) and $\vec{d}$ is the magnetic disturbance generated by surroundings.

$$\vec{H_{ext}} = \vec{H_{system}} + \vec{d} \tag{2}$$

It is assumed that the contribution of $\vec{H_{system}}$ is removed from the raw measurement during sensor calibration. As $\vec{d}$ cannot be measured directly, it has to be estimated indirectly.

We will now develop the notation used in the description of the heading estimation system. B and N denote a reference frame attached to the sensor module, and an absolute reference frame on the ground respectively. The following equation can be used to transform a 3×1 column vector ($\vec{x}$) from its representation in N ($\vec{x}^n$) to its representation in B ($\vec{x}^b$).

$$\vec{x}^b = C_n^b(q)\vec{x}^n \tag{3}$$

where $C_n^b(q)$, the direction cosine matrix, is obtained from the quaternion q.

We will now describe the Extended Kalman Filter. The state vector for the Extended Kalman Filter is composed of the rotation quaternion ($q = [q_1, q_2, q_3, q_4]$), augmented by tri-axial gyroscope scale ($s = [s_x, s_y, s_z]$) and bias factors ($\vec{b} = [b_x, b_y, b_z]$) and external magnetic disturbance vector ($\vec{d}^n = [d_x, d_y, d_z]$).

State Prediction Step In this step the state vector is projected ahead using the gyroscope readings. Gyroscope scale and bias factors, and the components of external magnetic disturbance vector are modeled as a random walk, given by,

$$s_{k+1} = s_k + {}^s w_k, \tag{4}$$

$$b_{k+1} = b_k + {}^b w_k, \tag{5}$$

$$\vec{d}_{k+1} = \vec{d}_k + {}^d w_k, \tag{6}$$

where ${}^s w_k, {}^b w_k, {}^d w_k$ are Gaussian noise terms.

As described in [16], for the discrete case the gyroscope readings can be incorporated by multiplying the attitude quaternion (q_k) by a quaternion (r_k) representing the change in orientation during the sampling period ΔT, given by,

$$q_{k+1} = q_k \otimes r_k, \tag{7}$$

where $\otimes$ represents quaternion multiplication and r_k is obtained from the gyroscope readings after correcting for scale and bias errors as follows.

$$r_k = \begin{bmatrix} a_c \\ a_s\sigma_x \\ a_s\sigma_y \\ a_s\sigma_z \end{bmatrix} \tag{8}$$

where

$$\sigma = \begin{bmatrix} \sigma_x \\ \sigma_y \\ \sigma_z \end{bmatrix} = \begin{bmatrix} (s_x\omega_x - {}^g b_x)\Delta T \\ (s_y\omega_y - {}^g b_y)\Delta T \\ (s_z\omega_z - {}^g b_z)\Delta T \end{bmatrix} + {}^g w_k, \tag{9}$$

and $[\omega_x, \omega_y, \omega_z]$ denotes the raw measurements of the gyroscope along x, y and z axes and ${}^g w_k$ is Gaussian noise. The values of a_c and a_s depend on the chosen order of approximation of quaternion integration [16]. We found that the first order approximation with $a_c = 1$ and $a_s = 1/2$ performs satisfactorily for a PDRS.

Measurement Update Step We assume the accelerometer and magnetometer measurement noise to be uncorrelated zero mean white noises. Independent update steps are performed for the magnetometer and accelerometer readings.

The magnetometer measurement (${}^m\vec{z}_{k+1}$) can be modeled as,

$${}^m\vec{z}_{k+1} = C_b^n(q_{k+1})(\vec{H}^n_{earth} + \vec{d}^n_{k+1}) + {}^m\vec{v}_{k+1}, \tag{10}$$

where $C_b^n(q_{k+1})$ is the reference frame transformation matrix derived from q_{k+1}, $\vec{H}^n_{earth}$ is the magnetic field due to Earth in ground reference frame, d^n_{k+1} is the estimated magnetic disturbance and ${}^m\vec{v}_{k+1}$ represents Gaussian noise.

The accelerometer measurement is used to perform a filter update only if the variance of accelerometer signal, computed over a running window of length 1 second is below a fixed threshold. It is assumed that if the accelerometer signal remains constant for a long time, then the user is at rest. Hence, acceleration measured by the accelerometer ($\vec{a}$) can assumed to be equal to gravity ($\vec{g}$). The accelerometer measurement in this condition (${}^a\vec{z}_{k+1}$) can be modeled as,

$${}^a\vec{z}_{k+1} = C_b^n(q_{k+1})(\vec{g}^n) + {}^a\vec{v}_{k+1}, \tag{11}$$

where $\vec{g}^n$ is the gravity vector in ground reference frame and ${}^a\vec{v}_{k+1}$ represents Gaussian noise.

III. Step Detection and Step Length Estimation

In this section we will describe the step detection and step length estimation techniques used to estimate the distance moved by the user.

A. Step Event Detection

We use a step event detection scheme based on the description given by Zijlstra et al. [14], [19]. We estimate the vertical displacement of the pelvis by double integrating the vertical acceleration. The vertical displacement thus obtained, however, has a large integration drift. In order to remove this drift, it is filtered using a zero-lag high-pass Butterworth filter with a cut-off frequency of 0.1 Hz. Steps are detected as peaks in the resulting vertical displacement. Once a step event is detected, the Initial Contact (IC) for the step is detected as a local maxima in the anterior-posterior acceleration preceding a zero-crossing.

B. Step Length Estimation

Several step length estimation techniques have been devised for different applications. Levi and Judd have described a technique in which step length is modeled as a linear function of step frequency [12]. Jeong et al. have described a method that does not need to be calibrated for different users. However, their method assumes that the IMU is worn near the foot [13]. Zijlstra et al. have described an inverted pendulum model for the motion of pelvis during a step [14]. This method requires the leg length to be measured experimentally and is known to be sensitive to user calibration [10]. Comparison of several popular step length estimation schemes reveal that the technique described by Wienberg et al. [11] is best suited for a waist mounted IMU using generalized calibration values [10].

The step length is given by the following equation,

$$L = K\sqrt[4]{a_{max} - a_{min}}, \tag{12}$$

where a_{max} and a_{min} denote the maximum and minimum vertical acceleration during a step respectively and K is a multiplication factor. The value of K is different for different people, and can be found out experimentally. We compute the values for a_{max} and a_{min} from the IC of each step to the IC of succeeding step.

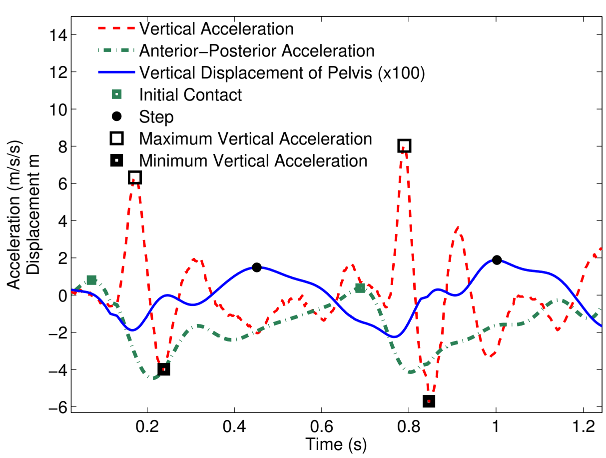

Fig. 2. Step Detection

Graph showing step event detection. The vertical displacement is multiplied by 100 to make it comparable to vertical and anterior-posterior acceleration.

IV. Indoor Experiments and Results

We used the iNemo IMU module developed by ST Microelectronics to collect data. The module is mounted on an adjustable waist belt (Figure 1). The module samples sensor data for a tri-axial accelerometer, a tri-axial gyroscope and a tri-axial magnetometer at 50Hz and transfers the raw data to a laptop over USB, which in turn timestamps and logs it. The collected data is processed offline using MATLAB.

Indoor experiments were performed in a corridor on the third floor of Bharti School of Telecommunication Technology and Management at Indian Institute of Technology Delhi. Figure 3 shows three different estimated trajectories for one of the experiments obtained by using only the gyroscope, only the magnetometer and the EKF filter as described above respectively. The scaling term K described in equation (12) was obtained by making the users walk a known distance. The total distance walked in the experiment in a total of 159 steps was 94.37m. The duration of the experiment was 88.6 seconds. We shall now describe each case in more detail. Similar results were obtained for other experiments and are omitted due to space constraints.

A. Gyroscope Only

User position was estimated using the proposed Extended Kalman Filter but with no updates performed for magnetometer measurements. It must, however, be noted that the accelerometer updates were performed as described in Section III. As expected, when the heading is estimated using only the gyroscope measurements the heading estimate starts drifting. The total error observed in the estimated position at the end of the experiment is 4.26m which translates to a 4.51% relative distance error.

B. Magnetometer Only

User position was estimated using only the magnetometer. The total error observed in the estimated position at the end of the experiment is 10.89m which translates to a 11.53% relative distance error.

C. Extended Kalman Filter using both Gyroscope and Magnetometer

The total error observed in the estimated position at the end of the experiment is 3.61m which translates to a 4% relative distance error. Although the relative distance error for this case is very similar to the case where only the gyroscope is used to estimate the heading, it can be seen in the figure that the average error in the estimated position, when measured over the entire path, is much worse for the latter.

V. Conclusions

We have presented a waist worn IMU based PDRS that requires minimal calibration on the user end. The obtained relative distance error of 4%, is encouraging and comparable to other handheld systems [15] and foot mounted systems [6].

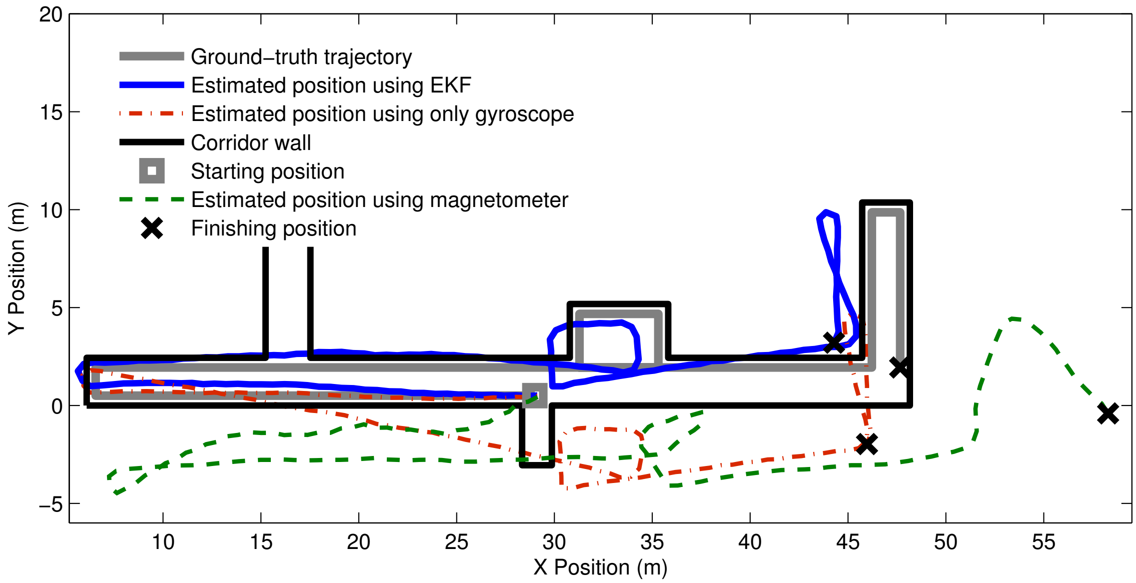

Fig. 3. Indoor Results

VI. Acknowledgements

This work was supported by Marvell India Pvt. Ltd. (grant number RP02134). We wish to thank Sandesh Goel and Yatin Acharya of Marvell for their guidance and support.

References

[1] C. M. Godha S., Lachapelle G., "Integrated GPS/INS system for Pedestrian Navigation in a Signal Degraded Environment," *Proceedings of the 19th International Technical Meeting of the Satellite Division of The Institute of Navigation (ION GNSS 2006)*, pp. 2151–2164, September 2006.

[2] Y. K. Thong, M. S. Woolfson, J. A. Crowe, B. R. Hayes-Gill, and D. A. Jones, "Numerical double integration of acceleration measurements in noise," *Measurement*, vol. 36, no. 1, pp. 73 – 92, 2004.

[3] Y. K. Thong, M. S. Woolfson, J. A. Crowe, B. R. Hayes-Gill, and R. E. Challis, "Dependence of inertial measurements of distance on accelerometer noise," *Measurement Science and Technology*, vol. 13, no. 8, p. 1163, 2002.

[4] S. Godha and G. Lachapelle, "Foot mounted inertial system for pedestrian navigation," *Measurement Science and Technology*, vol. 19, no. 7, p. 075202, 2008.

[5] S. Y. Cho and C. G. Park, "MEMS Based Pedestrian Navigation System," *The Journal of Navigation*, vol. 59, no. 01, pp. 135–153, 2006.

[6] R. Feliz, E. Zalama, and J. Gomez, "Pedestrian tracking using inertial sensors." Red de Agentes Fsicos, 2009.

[7] A. Jimenez, F. Seco, C. Prieto, and J. Guevara, "A comparison of Pedestrian Dead-Reckoning algorithms using a low-cost MEMS IMU," Aug. 2009, pp. 37 –42.

[8] S. Beauregard, "Omnidirectional Pedestrian Navigation for First Responders," Mar. 2007, pp. 33 –36.

[9] N. Castaneda and S. Lamy-Perbal, "An improved shoe-mounted inertial navigation system," in *Indoor Positioning and Indoor Navigation (IPIN), 2010 International Conference on*, 2010, pp. 1 –6.

[10] J. Jahn, U. Batzer, J. Seitz, L. Patino-Studencka, and J. Gutie andrrez Boronat, "Comparison and evaluation of acceleration based step length estimators for handheld devices," in *Indoor Positioning and Indoor Navigation (IPIN), 2010 International Conference on*, 2010, pp. 1 –6.

[11] H. Wienberg, "Using the ADXL202 in Pedometer and Personal Navigation Applications," *Analog Devices AN-602 application note*, 2002.

[12] J. T. Levi, Robert W., "Dead reckoning navigational system using accelerometer to measure foot impacts," Patent 5 583 776, December, 1996.

[13] Kim J.W, Jang H., Hwang D-H, and Park C., "A step, stride and heading determination for the Pedestrian Navigation System," *Journal of Global Positioning Systems, vol. 3*, pp. 273–279.

[14] W. Zijlstra and A. L. Hof, "Displacement of the pelvis during human walking: experimental data and model predictions," *Gait & Posture*, vol. 6, no. 3, pp. 249 – 262, 1997.

[15] D. Gusenbauer, C. Isert, and J. Kro andsche, "Self-contained indoor positioning on off-the-shelf mobile devices," in *Indoor Positioning and Indoor Navigation (IPIN), 2010 International Conference on*, 2010, pp. 1 –9.

[16] D. Titterton and J. Weston, *Strapdown Inertial Navigation Technology*, 2nd ed. The American Institute of Aeronautics and Astronautics, 2004.

[17] D. Roetenberg, H. Luinge, and P. Veltink, "Inertial and magnetic sensing of human movement near ferromagnetic materials," in *ISMAR '03: Proceedings of the 2nd IEEE/ACM International Symposium on Mixed and Augmented Reality*. Washington, DC, USA: IEEE Computer Society, 2003, pp. 268–269.

[18] A. M. Sabatini, "Quaternion-based extended Kalman filter for determining orientation by inertial and magnetic sensing," vol. 53, no. 7, pp. 1346–1356, 2006.

[19] W. Zijlstra, "Assessment of spatio-temporal parameters during unconstrained walking," *European Journal of Applied Physiology*, vol. 92, pp. 39 – 44, 2004.