Robust Misalignment Handling in Pedestrian Dead Reckoning

Published in
IEEE Vehicular Technology Conference

DOI
10.1109/VTCFall.2016.7881205

Robust Misalignment Handling in Pedestrian Dead Reckoning

Jayaprasad Bojja,*, Jussi Parviainen*, Jussi Collin*, Riku Hellevaara†, Jani Käppi†, Kimmo Alanen† and Jarmo Takala*,
*Department of Pervasive Computing, Tampere University of Technology, Finland
†Microsoft Corporation, Tampere, Finland

***Abstract*—Modern mobile devices consists various sensors such as accelerometers and gyroscopes that can be used to aid and complement Global Navigation Satellite System position and velocity updates. Especially these sensors are now capable of providing good navigation solutions for pedestrians with competitive battery power consumption when compared to radio navigation systems. In order to achieve this energy efficiency, the navigation solutions could primarily be based on onboard inertial sensors alone, and additional aiding systems such as GNSS or indoor map used only when requested, such as to initialize the starting position. One of the most critical problems in such mobile device navigation solutions is the inability to accurately estimate the misalignment between the pedestrian walking direction and the mobile device orientation, eventually causing the navigation algorithm to output wrong location solution. In this paper we propose methods to detect such situations and means to reduce the errors due to the misalignment estimation error.**

***Index Terms*—GNSS aided pedestrian dead reckoning, Inertial sensors, Mobile device, Frequency domain analysis, Principal component analysis.**

I. Introduction

Pedestrian dead reckoning (PDR) is a method of estimating the position of a pedestrian, by accumulating the position using estimated heading and distance traveled. The primary device used in PDR is inertial measurement unit (IMU), consisting of inertial sensors, namely, accelerometers and gyroscopes. There are many form factors of such IMU devices, used for a variety of applications [1]–[3]. The IMUs used for PDR are mostly fixed to the pedestrian in known location such as waist, or shoes.

A common platform for PDR system consists of mobile device with IMU and global navigation satellite system (GNSS) receiver, which provides absolute updates to PDR algorithm. The native coordinate frames of PDR and GNSS are not aligned and this brings up the misalignment problem. With mobile devices, the users can carry the device in hand in different orientations, for example turning or swinging the phone while walking. Often the device is kept in pocket and then picked up to answer a phone call. There are many ongoing research works on PDR using mobile devices to solve the indoor positioning problem [4]–[6], and problems caused by unknown alignment between the pedestrian and the mobile device are well known. Various methods to align the PDR coordinate frames have been proposed [7]–[9]. However, these methods are not perfect and identification of a misalignment problem would be necessary for the navigation filter.

In this paper, we propose methods to detect and compensate mobile device misalignment, when the aiding information, such as GNSS or indoor map, is available and provide some alternative methods to handle or overcome such situations. We use a mobile device for GNSS aided PDR experiments and show the feasibility of the methods. The paper is organized as follows. In section II, the theoretical background of PDR systems with the onboard IMUs of mobile devices is reviewed. Section III discusses the mobile device alignment with pedestrian walking direction and section IV considers methods to detect and mitigate the misalignment problem. In section V, we elaborate on the experiments conducted and discuss about various methods, and section VI concludes this paper.

II. Theorical Background

PDR is achieved by utilizing the kinematics of human gait [10]. Traditionally, the pedestrians step count, step length and heading are estimated and, after that, dead reckoning algorithm is used to provide the current location of a pedestrian [11]. Conventionally, the steps are detected using the norm of accelerometer triad, a_{norm}, as

$$a_{norm} = \sqrt{(a_x^2 + a_z^2 + a_z^2)}, \tag{1}$$

where a_x, a_y and a_z are the components accelerometer triad. By detecting the cyclic pattern of the pedestrian signal, the travelled distance, r_n can be calculated by accumulating estimated step displacement Δs at each time instance i,

$$r_n = \sum_{i=1}^{n} \Delta s_i. \tag{2}$$

Heading, i.e., yaw angle, Ψ, is estimated using gyroscopes and/or digital compasses (magnetometers). Conventionally, in order to calculate the heading, full 3-dimensional attitude of the IMU needs to be estimated. This can be done, e.g., using rotation matrices or quaternions [12]. In this paper, we assume that the attitude estimation is done, and we simplify the problem by assuming that we have (virtual) gyroscope reading, ω, measuring the yaw angle. Thus, heading can be estimated as

$$\Psi_n = \Psi_{n-1} + \omega_{n-1}\delta t, \tag{3}$$

where δt is sampling rate. There exist various methods for step detection, including peak detection, zero-crossing, auto-correlation, and fast Fourier transform. A PDR propagation equation is described in [13, section 2]. Since PDR is a relative position method, the initial position of the pedestrian must be known. This is usually done by filtering PDR with GNSS (when outdoors) and WLAN-based positioning (when indoors), switching the filter operation mode based on available inputs. When the filter enters pure PDR mode, the state from other modes is used as initial reference state [14]. The step detection algorithms vary depending on the location of the measurement sensor with respect to the pedestrian. Some options for the PDR are to use the IMUs mounted in pedestrians pocket or torso [15]–[17], and other option is to mount the IMU rigidly with respect to the pedestrian, for example, pedestrians shoe [18], [19]. Foot based solutions have shown to be very effective due to the periodic zero velocity updates and zero angular rate updates which can be obtained during the stance phase, i.e. when the foot is flat on the ground [20]. With mobile devices the placement cannot be controlled, and, in addition to misalignment problem, the step length estimates are potentially biased due to wrong placement assumption. Thus GNSS or another update source plays a significant role in mobile device PDR. Conventionally, information from GNSS is used to aid PDR when available. The GNSS locations can be transformed to pedestrian centered East, North and Up (ENU) coordinate system depicted in Fig 1, and then the GNSS measurement update equation is simply

$$\mathbf{y}_n = \left[E_n^{GNSS}\ N_n^{GNSS}\ \Psi_n^{GNSS}\right]^T, \tag{4}$$

where E_n^{GNSS}, N_n^{GNSS} are east and north components of 2D position, and Ψ_n^{GNSS} is the heading measurements obtained from by the GNSS. It should be noted that GNSS heading update is quite noisy at low speeds and uninformative when the receiver is stationary. The following equations describe a simple GNSS aided PDR using extended Kalman filter (EKF), where the IMU is mounted in a fixed position with respect to the pedestrian. Refer [21, section 5.2] for EKF in general. EKF algorithm for GNSS aided PDR includes prorogation phase

$$\begin{aligned}\mathbf{x}_n &= \begin{bmatrix} E_n \\ N_n \\ \Psi_n \end{bmatrix} = f\left(\begin{bmatrix} E_{n-1} \\ N_{n-1} \\ \Psi_{n-1} \end{bmatrix}\right) \\ &= \begin{bmatrix} E_{n-1} + \Delta s_{n-1}\cos(\Psi_{n-1}) \\ N_{n-1} + \Delta s_{n-1}\sin(\Psi_{n-1}) \\ \Psi_{n-1} + \omega_{n-1}\delta t \end{bmatrix}\end{aligned} \tag{5}$$

$$\mathbf{P}_n = \mathbf{F}_{n-1}\mathbf{P}_{n-1}\mathbf{F}_{n-1}^T + \mathbf{Q}_{n-1} \tag{6}$$

and update phase

$$\boldsymbol{\xi}_n = \mathbf{y}_n - \mathbf{H}\mathbf{x}_n \tag{7}$$

$$\mathbf{S}_n = \mathbf{H}_n\mathbf{P}_n\mathbf{H}_n^T + \mathbf{R}_n \tag{8}$$

$$\mathbf{K}_n = \mathbf{P}_n\mathbf{H}_n^{'}\mathbf{S}_n^{-1} \tag{9}$$

$$\mathbf{P}_n = \mathbf{P}_n - \mathbf{K}_n\mathbf{H}_n\mathbf{P}_n \tag{10}$$

$$\mathbf{x}_n = \mathbf{x}_n + \mathbf{K}_n\boldsymbol{\xi}_n, \tag{11}$$

where f is the dynamic state model, $\mathbf{F}$ is the Jacobian of f. Symbol $\mathbf{H}$ is the measurement model matrix, which is in this case identity matrix. $\mathbf{Q}_n$, $\mathbf{R}_n$ are process and measurement Gaussian noise covariance matrices, $\mathbf{P}_n$ is error covariance of state $\mathbf{x}_n$, ξ_n is prediction error w.r.t to the measurement y_n, $\mathbf{S}_n$ is the covariance of prediction error and $\mathbf{K}_n$ is the Kalman gain, at time instance n.

III. Smartphone Alignment with Pedestrian

If the PDR method is applied in hand held devices, such as mobile phones and tablets, the assumption of fixed location does not necessarily hold. Thus for these scenarios, one problem is that the measurement device frame is not aligned with the pedestrian frame, as it is enlightened in Fig 2. As the figure illustrates the signals measured in the device are not aligned with the pedestrian and mobile device may move regardless of the pedestrian frame. Thus the direction of travel offset alignment between the pedestrian and mobile device frame must be resolved and compensated to the heading estimated as in (3) with pure gyro measurements. The signal pattern is very different depending on how the user is carrying the measurement device, for example in the hand fixed and looking at the device screen, in the hand fixed and swinging, or in the pocket.

To tackle this misalignment problem, various methods to account different carrying modes of device have been proposed [22]–[28]. Kourogi et al. [23] explain the wave form of the vertical and forward acceleration and they present the principal component analysis (PCA) based method for the direction sensing. In [24] authors show that stance phase of the step has more accurate information about direction. Ayub et al. [25] proposed method for integrated speeds of horizontal axes and to use arctangent to yield the direction of travel. Pai et al. [26] use map matching and particle filtering to estimate the direction of travel. In [27] variances of horizontal plane are used to detect the direction of travel. In [28] radio receiver

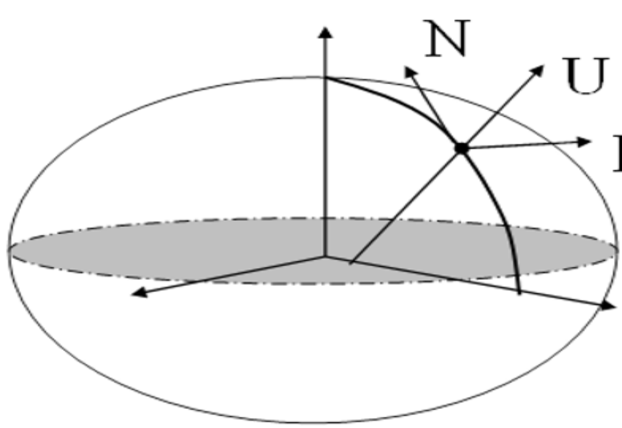

Fig. 1. Earth tangential coordinate frame, East, North and Up

signals are used to estimate the pedestrians direction of travel. A frequency domain method for determining the pedestrian walking direction is proposed in [7]. Then similar frequency domain processing method was proposed in [8].

The problem that could appear in most of the previously discussed methods is that there is a tendency for the PDR to fail in certain scenarios such as walking on stair cases. This kind of problem has been observed during our experiments to test our direction of travel algorithm. Fig. 3 shows a general PDR flow chart which depicts where a misalignment adjustment block would appear in an assisted PDR algorithm.

IV. Detecting and Correcting Misalignment

When the aiding information for PDR is available we are able to detect when the misalignment detection is giving incorrect solutions. If the misalignment estimation goes wrong it may effect badly to all the states in the PDR filter. For example, the bias estimation of the gyros, which is one of the critical issues in PDR, may go wrong when misalignment goes wrong. To detect and correct when misalignment is incorrectly estimated, we can use some of the following proposed methods.

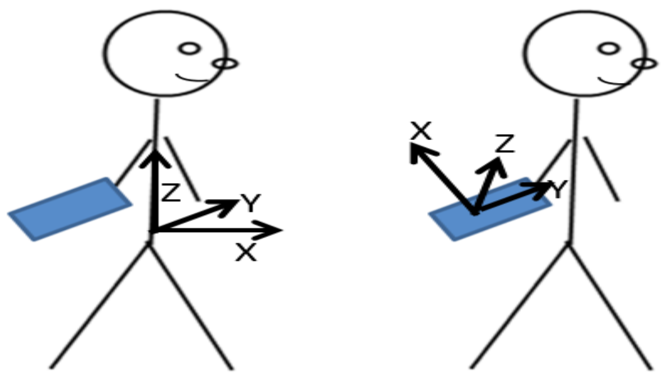

Fig. 2. Coordinate frame of pedestrian, i.e. walking frame where x-axis is the direction of travel (left), and Coordinate frame of device, where inertial sensor measurements are obtained (right)

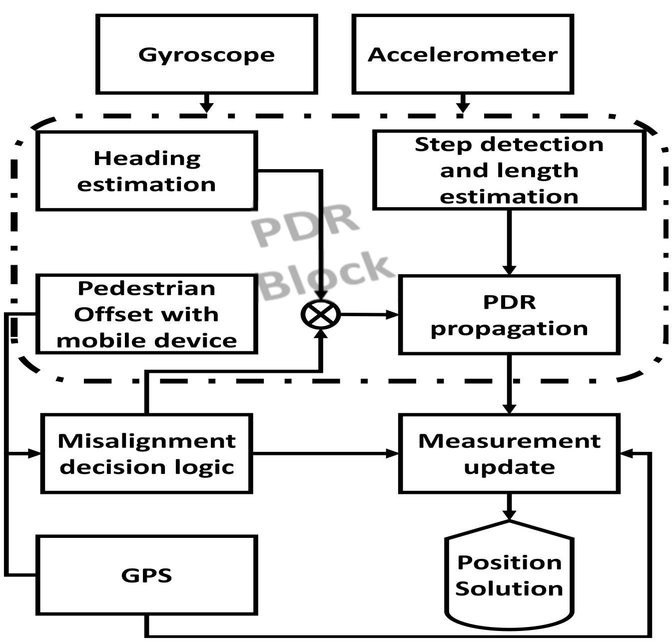

Fig. 3. Block diagram of a PDR with misalignment block

A. Misalignment Detection

Probably the easiest way is to use GNSS heading information directly and compare that to the estimated PDR heading. However, this method is quite simplistic as the only heading information is used. Better method would be to take into account also information from the covariances. This can be done by using the normalized innovation of PDR Kalman filter, which can be written in a Mahalanobis distance form as

$$m = \boldsymbol{\xi}_n^T S^{-1} \boldsymbol{\xi}_n \tag{12}$$

or in a vector form as

$$\boldsymbol{\epsilon} = \left(\sqrt{\mathbf{S}_n}\right)^{-1} \boldsymbol{\xi}_n \tag{13}$$

such that $\boldsymbol{\epsilon} = [\epsilon_E \ \epsilon_N \ \epsilon_\Psi \ \cdots]^T$ includes all the normalized state variables.

When there is large change in innovation, it could be due to false heading estimation in PDR. Only innovation from the heading component, ϵ_Ψ, can be used or the full information from all the components of $\boldsymbol{\epsilon}_n$. In order to do this we need to calculate the zero mean normal distributions

$$N(\epsilon_i, \sigma) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\epsilon_i^2}{2\sigma^2}\right) \tag{14}$$

for all components ϵ_i of $\boldsymbol{\epsilon}$ using standard deviation $\sigma = 1$. Then, the combined weight t can be calculated as

$$t = \log \prod_i N(\epsilon_i, \sigma) \tag{15}$$

This weight can also be calculated from multiple time instances, thus we can write according to [29] as

$$t_{sum} = \sum_n \left(\log \prod_i N(\epsilon_i, \sigma) \right). \tag{16}$$

B. Correcting Misalignment

When we have detected that there is an error in the misalignment estimation, we can use at least following methods to correct the situation

- Increase variance in the covariance matrix of the heading state
- Run the filter with multiple different heading estimates. This leads us using for example marginalized particle filter (MPF) as it was used in [30], to initialize the yaw angle of the smartphone IMU with respect to a vehicles in order to align the smartphone with the vehicle
- Reset the PDR filter

Increasing the variance could be done just by scaling the covariance matrix with a constant or use equivalently the

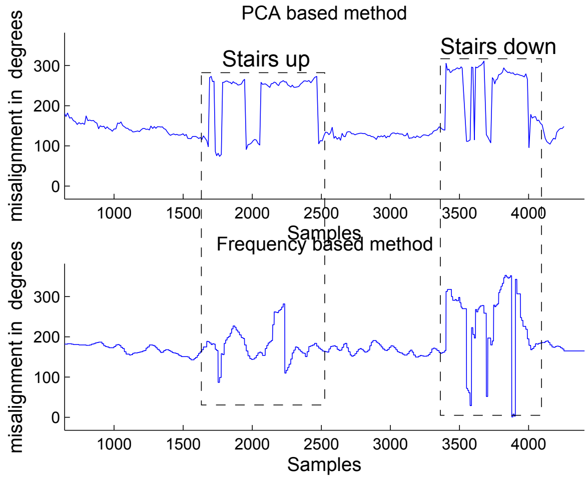

Fig. 4. Walking stairs when device is in fixed position respect to body using PCA and frequency based misalignment method

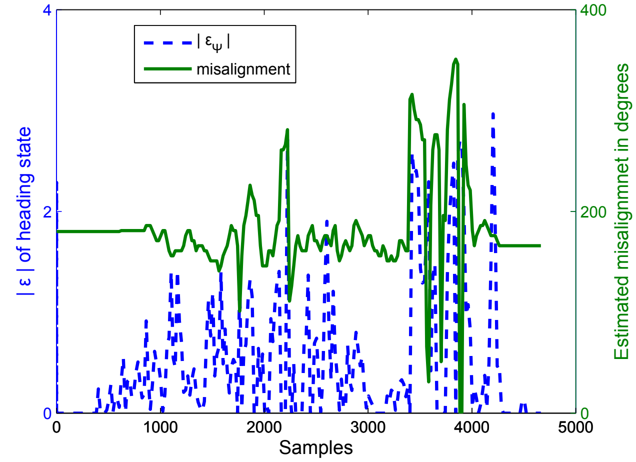

Fig. 5. Absolute value of normalized innovation of heading value $|\epsilon_\Psi|$ using frequency based method

methods for adaptive Kalman filtering [31]. Increasing the variance and resetting the filter totally would be the most light weight solution. However, the accuracy of the estimated states will degenerate. Particle based solutions, such as MPF, where in the yaw angle computed, will need more computations, but the accuracy of all the states will remain the same almost all the time instances. It should be noted that it is not straight forward to estimate the misalignment with any method, as the other error sources, such as gyro bias, are also affecting to the end result.

V. Experiments and Discussion

Some preliminary experiments were conducted using mobile device carried in the hand and walking up and then down the stairs. Fig. 4 shows the misalignment angles evaluated from this test data using PCA based [23] and frequency domain analysis [7] methods. During the test, the phone was held in hand with a fixed misalignment angle, i.e., the misalignment algorithms should show constant value, which was in this test around 180 degrees. However, the error of the algorithms output increases when walking on the stairs in both directions.

For frequency based method, the standard deviation and mean, when walking on a flat ground are $\sigma_{flat} = 10$ and $\mu_{flat} = 166$ degrees and when walking on stairs up and down are, $\sigma_{up} = 37$ and $\mu_{up} = 179$, $\sigma_{down} = 91$ and $\mu_{down} = 246$. These observed values are illustrated in lower part of Fig. 4. Similarly, the results for the PCA based method are illustrated in upper part of Fig. 4, and the corresponding numbers are $\sigma_{flat} = 9.2$ and $\mu_{flat} = 128$ degrees and $\sigma_{up} = 70$ and $\mu_{up} = 212$, $\sigma_{down} = 64$ and $\mu_{down} = 257$. In this case, as we can see that the standard deviation, σ, of misalignment estimation increases drastically when the user is walking on the stairs. In PCA type solution the error follows more bias type error, where the solution jumps 180 degrees, whereas frequency based solution has more like randomly varying error. Thus, high value of standard deviation in misalignment estimation can be indeed one indicator for the system not to use the misalignment estimation at all. Fig. 5 illustrates the estimated frequency based method and absolute value of normalized innovation of heading value $|\epsilon_\Psi|$ and Fig. 6 illustrates same information using PCA method. We can see that $|\epsilon_\Psi|$ value grows, as expected, and there is a large error in misalignment estimation. The growth is even more visible in PCA method where the errors are also more rapidly changing. When we detect, that we have large value in our normalized innovation or even the variance of the estimated innovation is high we can take actions as we proposed in section IV-B. It should be noted that the innovation of filter may also be the cause of errors in yaw angle estimation; however, those are not usually as drastic as the false misalignment estimation would give.

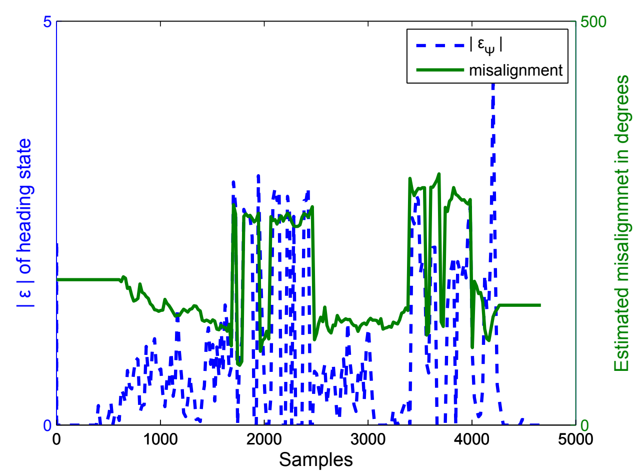

Fig. 6. Absolute value of normalized innovation of heading value $|\epsilon_\Psi|$ using PCA based method

VI. Conclusion

We showed methods to detect and ways to handle the errors in misalignment in PDR, when GNSS aiding information available. Methods are based on the innovation of the GNSS and PDR fusion Kalman filter. Results showed that normalized innovation of the heading state could be one option for the parameter. It should be noted that different types of errors may also infer to innovation states, and the filters with different number of state variables may affect to solution. The results indicate, that we can use an adjustable threshold to detect when there is error in misalignment estimation and then actions to correct solutions can quickly be triggered. As a future work, instead of finding errors, one option would be to combine different types of misalignment algorithms or change the algorithm dynamically. For example, if walking on stairs is detected, accordingly a method that that is working best in that case is applied. Further research is needed to figure out how to efficiently isolate misalignment errors from other error sources. Arguably, the effective misalignment estimation is one the remaining challenges in PDR for mobile devices.

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