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Robust Pedestrian Dead Reckoning for Multiple Poses in Smartphones

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ABSTRACT In this paper, an integration approach (IA) and parametric approach (PA) fusion-based pedestrian dead reckoning (PDR) using low-cost inertial sensors is proposed to improve the indoor position estimation. When moving indoors using a smartphone, various poses such as texting and putting a pocket are possible. In the existing PA-based positioning algorithms, it can be used only when the pedestrian's walking direction and the device's direction coincide. In order to solve the problem, this paper proposes an algorithm that constructs state variables based on the IA and uses the position vector from the PA as a measurement. If the walking direction and the device heading do not match based on the poses, the position is updated according to the direction calculated using principal component analysis (PCA) and the step length obtained from the PA. Through experiments considering various operating conditions and paths, it shows that the proposed method stably estimates the position and improves performance even in various indoor environments with the accuracy of 2.13m for Xsens MTw 2.49m for Smartphone.

INDEX TERMS Indoor navigation, pedestrian dead reckoning (PDR), extended Kalman filter (EKF), integration approach (IA), parametric approach (PA), fusion method.

I. INTRODUCTION

Indoor navigation has been actively studied as the growing number of people desires to locate themselves through smart devices. Unlike outdoor navigation, a global positioning system (GPS) is not available in an indoor environment due to inadequate coverage of the satellite signal and multi-path errors, various alternatives are presented with additional sensors or methods [1]–[4]. A direct sensing-based localization tracks the position of a pedestrian by the sensing of identifiers or tags installed in the environment before experiments [5]. These include radio-frequency identification (RFID), infrared (IR), Ultrasound, and Bluetooth. With regard to pattern-recognition-based localization, well-known examples are WLAN and magnetic map-based fingerprinting [5], [6]. Dead reckoning (DR)-based localization, one of the alternatives, uses sensors attached to the users to estimate relative positions based on the previous or known position [7]. A benefit of the DR approach is low installation cost and does not require any additional sensors, but accumulated position errors are a significant problem of this technique [8].

Localization using DR is primarily categorized as an integration approach (IA) and a parametric approach (PA). For the tracking with shoe-mounted inertial sensors, the IA-based system that estimates the current position by integrating acceleration is applicable. It is because one of the strong pseudo-measurements, zero velocity update (ZUPT), allow estimating those inertial sensor errors under the assumption that the velocity of a foot being zero during the stance phase [9]–[12]. When the sensor is held on hand such as smartphones, on the other hand, the PA system that estimates position by step detection, step length estimation, and heading estimation is applied instead of the IA [13]. To estimate the heading of a device is an essential part of the PA, and the attitude estimation using the angular rate from the gyroscope, the specific force from the accelerometer, magnetic field from the magnetometer are called attitude heading reference system (AHRS). Using the characteristics that gyro measure has a low-frequency component, and accelerometer and magnetometer have high-frequency one, the AHRS

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combines those sensors with filtering methods such as complementary filter and Kalman filter. However, its performance degrades, especially when the sensor is moving fast or exposed to a magnetic disturbance.

The framework of combining PA and IA is discussed in [14]–[16]. In order to overcome the poor quality of built-in inertial sensors in commercial smartphones, pseudo velocity measurements during steps are used in [14], [15]. Similarly, pseudo velocity and position measurements are selectively used according to the holding mode in [16]. These papers show the effectiveness of combining PA and IA in the various aspects, but the heading mismatch during poses other than text pose depends only on the position from the navigation which is erroneous in many cases without measurement updates.

In this paper, in order to overcome the limitations of conventional PA-based pedestrian dead reckoning (PDR) in the smartphone, the integration of IA and PA is proposed. Specifically, navigation error states of the IA are estimated using the attitude and step length from the PA. With the help of the estimated device attitude and poses, it is possible to recognize the device heading and the walking direction mismatch situations. Then, the walking direction acquired from the principal component analysis (PCA) of tangential acceleration data is used to update the IA states. The proposed algorithm is operated even in various poses that occur when a pedestrian moves with a smartphone indoors. The contribution of this study can be summarized as follows:

- IA and PA-based PDR algorithm for position estimation using the extended Kalman filter (EKF) is designed. The states of IA are estimated using measurements from ZUPT, AHRS, PA, and PCA. The PCA of tangential acceleration during a stride is performed when the walking direction and device attitude do not coincide to find the walking direction.
- The classified four poses (text, shirt pocket, trouser pocket, and swing) allow finding the three measurement updating modes: transition, match, and mismatch.
- The proposed algorithms can be applied in various fields such as smartphone users in the buildings, first responders, virtual and augmented reality.

The remaining paper consists of the following: The state-of-art works of the conventional approaches are introduced in Section 2. In Section 3, the IA and PA-based PDR system is described. Section 4 presents the specific logic of the IA and PA fusion PDR system. The experimental results discussed are presented in Section 5, and the conclusion is described in Section 6.

II. RELATED WORKS

Pedestrian navigation using inertial sensors has been used in a wide range of fields, including ambulatory human motion analysis. Micromachined gyroscopes and accelerometers are used in many applications such as monitoring daily living activities [17]–[19], evaluating internal mechanical workload in ergonomic studies [20]–[23], measuring nervous system disorders [24]–[27], and mixed and augmented reality [28]–[30]. This section of related works focuses on position estimation under multiple poses of the smartphone. It is important to estimate walking directions of the multi-action correctly because handheld smartphones are usually unrestricted and often have device heading changes that do not match the direction of walking. In the PA-based PDR system, the small heading difference leads to a large position error. In order to remove the heading offset between them, some researchers have attempted to solve this problem [31]–[39]. In [31], the various PCA-based walking direction estimation methods are compared with broad experimental study in case of pocket. To be specific, the PCA2D (2D acceleration projected on the global horizontal place), PCA2Df (same as PCA2D but lowpass filtered data with 5Hz before PCA), PCA3Df (PCA to 3D acceleration axes with the 3rd eigenvector for walking direction), and gyroPCA (PCA to the 3D rotational vector axes). The reference [32] uses thresholds and a rotating axis for swing, call, trouser pocket poses to find out the offset angle in the smartphone. In [33], the author proposes adaptive offset compensation under the swing, holding, and trouser pocket modes. The heading offset for each mode is compensated by remembering the heading in a straight holding condition. The PCA-global acceleration (GA) method is proposed for heading estimation during a mismatch condition in [34] by assuming that the least varying acceleration axis during a stride is perpendicular to the walking direction. In addition, heading estimation using PCA is proposed in [35], [36] by introducing several coordinate systems: user, device, reference which is an initially aligned plane, and global.

In case of finding out the heading mismatch condition, machine learning technique such as decision tree (DT), support vector machine (SVM), or finite state machine (FSM) is commonly used. Also, a learning-based localization algorithm is proposed by determining step length and walking direction using an online sequential extreme learning machine (OS-ELM) [37]. The walking direction calculated from frequency-domain features of projected acceleration is also proposed [38]. In addition in [39], the gradient descent algorithm (GDA) is proposed for heading estimation of the smartphone in the trouser pocket.

In the above conventional PDR systems for multiple poses of the smartphone, fixed or only PCA angles are used to eliminate the heading difference. The fixed offset angle causes a large error when the pose does not last equally for each step. In addition, when walking indoors, there are errors that occur when switching motions and rotating at the corner. In order to solve such erroneous situations, the IA, PA, and PCA are fused by means of filters to obtain better position results in this paper.

III. IA AND PA BASED PDR SYSTEM

PDR is a dead reckoning system that makes the assumption that the position of a pedestrian is changed by steps. Based on this, the PDR estimates the location of the pedestrian by observing the movement of steps. Depending on the position of the installed sensor, the PDR system can be classified into the IA and PA. The following subsections explain those in detail.

A. PA-BASED PDR

The PA-based PDR is a pedestrian-dependent method and estimates its position with heading and distance between steps. In general, the algorithm is composed of a step detection, a step length estimation, and a heading estimation [13], [40]. Each component of the PA-based PDR is described as follows.

1) STEP DETECTION ALGORITHM

The first step in PA-based PDR is to identify steps. Step detection is usually an easy problem, but if there are have false or miss detections, or if the smartphone's action varies, there are significant errors when estimating overall walking distance. Therefore, accurate step detection is the basis on which an accurate estimation of the position can be made in the PDR method.

When it comes to navigating with a smartphone or tablet, placements of the device should be considered for step detection. According to the [41], [42], the possible placements for unconstrained smartphones include handheld, texting, calling, trouser back and front pocket, handbag, backpack, and shirt pocket, and those are usually classified through machine learning techniques.

In this paper, the norm of a 3-axis acceleration is used for the step detection algorithm as (1) [34], [43]. It is because it is not affected by the sensor attitude that could be changed following pose changes.

$$f_{norm} = \sqrt{f_x^2 + f_y^2 + f_z^2} \tag{1}$$

where f_{norm} is the acceleration norm, and f_x, f_y, and f_z denote the output of 3-axis accelerometer in x, y, and z-axis, respectively. Then, the sliding window sum of the norm data is used to reduce noise in step detection as follows.

$$SWS(k) = \sum_{t=k-N+1}^{k} f_{norm}(t) \tag{2}$$

where SWS and N represent the sliding window sum and the window size set as 15 for this paper. The window size is usually set smaller than the duration of the detected phase.

Then, the peak of the SWS can be recognized as a step. The peak detection method detects the heel-strike which is the moment the foot touches the ground, allowing to find a step periodically. In this paper, considering the advantage of accurate heel strike detection, a peak detection method using acceleration is used. The acceleration data is low-pass filtered with a cutoff frequency set to 5 Hz and windowed to prevent noise effects. In the case of peak detection-based step detection, the position is estimated at every step. Due to the characteristics of the poses, especially in the trouser pocket and swing, a position error occurs when estimating position in every step. Therefore, the position is estimated based on two steps, that is, one stride in this paper.

2) STEP LENGTH ESTIMATION ALGORITHM

Step length estimation can be divided into two main classes: direct and indirect methods [44]. The direct methods estimate the stride length directly through integration. On the other hand, the indirect methods estimate step length using a model. These methods are also divided into geometric and statistical models. The first uses the biomechanical characteristics of the human body. This includes the inverted pendulum model and empirical model. In case of the statistical regression method commonly used for a smartphone, variables such as walking frequency (WF) and acceleration variance (AV) are usually used, and the relationships among variables are estimated through parametric or non-parametric techniques. A linear regression model is one of the representative methods in the PA [42], [45]–[48].

There are many features other than the walking frequency, but it is advantageous for the independence of the mounting position as long as the step is accurately detected. The following (3) is the step length formula applied.

$$SL = \alpha \cdot WF + \beta \tag{3}$$

where WF is walking frequency and α, β are pre-learned parameters according to the pre-calibration.

3) HEADING ESTIMATION

Estimating the orientation of the device is an essential part of the PA, and the AHRS estimates the attitude using the angular rate from the gyroscope, the specific force from the accelerometer, magnetic field from the magnetometer. As long as there is no acceleration and magnetic disturbance, roll and pitch of the accelerometer and yaw of the magnetometer can be calculated.

In case of additional acceleration or magnetic disturbance, it is essential to deal with the acceleration or residual magnetic field. Therefore, an adaptive algorithm using the ellipsoid method for residuals was proposed in a previous study [49]. Specifically, the algorithm adjusts the measurement covariances taking into account the direction of these residuals.

Given two ellipsoids E_1 and E_2, one is the measurement covariance without acceleration and the other is the one with acceleration. The goal is to find the third ellipsoid E containing both ellipsoids using the ellipsoidal method [49], [50]. Assume that the ellipsoid (E_1) is defined as (4) with the set of all $\mathbf{p}$ on ellipsoid (E_1) centered around the mean ($\mathbf{m}_1$) and covariance ($\mathbf{R}_1$).

$$E_1 \equiv \left\{ \mathbf{p} | \left(\mathbf{p} - \mathbf{m}_1\right)^T \mathbf{R}_1^{-1} \left(\mathbf{p} - \mathbf{m}_1\right) \leq 1 \right\} \tag{4}$$

The ellipsoid E_2 and E are defined in the same way. The corresponding mean and covariance of covering ellipsoids, E, can be calculated by means of E_0, which is as follows:

$$\mathbf{m} = \mathbf{m}_0 = \frac{1}{2}\left(\mathbf{m}_1 + \mathbf{m}_2\right) \tag{5}$$

$$\mathbf{R}^{-1} = \alpha\mathbf{R}_0^{-1} = \alpha\left(\mathbf{R}_1 + \mathbf{R}_2 + \frac{1}{4}\lfloor\mathbf{m}_1 - \mathbf{m}_2\rfloor\lfloor\mathbf{m}_1 - \mathbf{m}_2\rfloor^T\right)^{-1} \quad (6)$$

where $\mathbf{R}_0$, is a covariance of the ellipsoid, the corresponding ellipsoid, E_0, and a positive parameter α is the adjusting factor for covariance.

The specific details about the adjusting covariances are explained in [49].

B. IA-BASED PDR

The IA-based PDR is a system that tracks the position by estimating the entire 3D trajectory of the sensor at a given moment. It is a simplified version of the inertial navigation system (INS) for the low-cost inertial sensors, so the basic structure is the same. The system calculates the position by integrating the acceleration and angular rate at given every sample, and the process consists of five steps: bias compensation, orientation updates, gravity removal, integration, and correction [51].

In the bias compensation step, the estimated accelerometer and gyro biases are subtracted in the raw sensor data as (7).

$$\begin{cases} \tilde{\boldsymbol{\omega}}_k^b = \mathbf{y}_{g,k}^b - \widehat{\boldsymbol{\varepsilon}}_{k-1}^b \\ \tilde{\mathbf{f}}_k^b = \mathbf{y}_{f,k}^b - \widehat{\nabla}_{k-1}^b \end{cases} \quad (7)$$

where $\tilde{\boldsymbol{\omega}}_k^b$ and $\tilde{\mathbf{f}}_k^b$ are compensated gyro and accelerometer in body frame, respectively, and $\mathbf{y}_{g,k}^b$ and $\mathbf{y}_{f,k}^b$ are raw inertial sensor output in body frame, and $\widehat{\boldsymbol{\varepsilon}}_{k-1}^b$ and $\widehat{\nabla}_{k-1}^b$ are estimated bias for gyro and accelerometer, respectively.

Next, attitude representing the relationship between body (b, defined as Forward-Right-Down) and navigation (n, defined as North-East-Down) frame is updated using the angular rate in quaternion attitude representation as (8).

$$\mathbf{q}_k = (\mathbf{I} + \frac{1}{2}\mathbf{W}\Delta t)\mathbf{q}_k$$

where

$$\mathbf{W} = \begin{bmatrix} 0 & -\tilde{\boldsymbol{\omega}}_k^b \\ (\tilde{\boldsymbol{\omega}}_k^b)^T & \left[-\tilde{\boldsymbol{\omega}}_k^b \times\right] \end{bmatrix} \quad (8)$$

where $\left[\tilde{\boldsymbol{\omega}}_k^b \times\right]$ is the skewsymmetric matrix, and $\mathbf{q}_k$ is a quaternion defined as $\mathbf{q}_k = \begin{bmatrix} q_{0,k} & \vec{\mathbf{q}}_k \end{bmatrix}^T = \begin{bmatrix} q_{0,k} & q_{1,k} & q_{2,k} & q_{3,k} \end{bmatrix}^T$.

In the third stage, gravitational component is removed from the compensated accelerometer as (9).

$$\bar{\mathbf{f}}^n = \mathbf{C}_{b,k}^n \tilde{\mathbf{f}}_k^b - \mathbf{g}^n \quad (9)$$

where $\mathbf{C}_{b,k}^n$ is a direction cosine matrix (DCM) transformed from the $\mathbf{q}_k$, and $\mathbf{g}^n$ is gravity represented in n-frame.

In the fourth stage, velocity and position are calculated through the integration as (10).

$$\begin{cases} \mathbf{v}_k^n = \mathbf{v}_{k-1}^n + \bar{\mathbf{f}}_k^n \cdot \Delta t \\ \mathbf{p}_k^n = \mathbf{p}_{k-1}^n + \mathbf{v}_k^n \cdot \Delta t \end{cases} \quad (10)$$

where Δt, $\mathbf{v}_k^n$, and $\mathbf{p}_k^n$ are sampling time, velocity, and position, respectively. The velocity model is simplified as above because the low-cost MEMS inertial measurement unit (IMU) does not measure the earth rotation rate and Coriolis effect.

The fifth stage is the correction from the EKF error states using the measurements. The EKF is implemented to integrate the IA and PA methods in this paper, and the correction is made following the estimated errors, which is discussed in the following subsections. In brief, the position, velocity, attitude, and biases for accelerometer and gyro are corrected with the EKF estimates.

IV. IA-PA FUSION ALGORITHM

In this section, a new approach for IA and PA-based PDR using PCA is presented [52]. Handheld smartphones are usually unrestricted and often have device heading changes that do not match the direction of walking. In order to solve the heading mismatch errors under multiple poses in PDR, the proposed algorithm takes the advantages of both IA and PA as in Fig. 1. The IA-based PDR calculates position, velocity, and attitude with acceleration and angular velocity by using integration, so it is able to find out walking direction in addition to the device heading. However, since PDR with IA generates errors quickly when using a low-cost inertial sensor, proper measurements are necessary to estimate the state of velocity, position, etc. Therefore, the step length and heading from the PA are used as measurements when the directions match. If the device direction does not coincide with the walking direction, the walking direction is calculated using the PCA of the horizontal acceleration in the navigation frame, and then the IA position is updated with PCA and step length from the PA.

The assumption used in constructing the algorithm in this paper is that in a walking scenario, the starting pose is always text, and the user standstills for few seconds in the beginning.

A. SYSTEM MODEL

The built-in inertial sensors and magnetometer from the smartphone are the input of the system, and 15 error states of EKF are position of one stride, velocity, attitude, accelerometer bias, and gyro bias as in (11).

$$\delta\mathbf{x} = \begin{bmatrix} \delta\mathbf{p}_{step}^n & \delta\mathbf{v}^n & \delta\boldsymbol{\varphi} & \widehat{\nabla}^b & \widehat{\boldsymbol{\varepsilon}}^b \end{bmatrix}^T \quad (11)$$

where the $\boldsymbol{\varphi}$ is attitude represented in Euler angle. The corresponding system matrix is in (12) following the relationship among states.

$$\boldsymbol{\Phi} = \begin{bmatrix} \mathbf{I}_{3\times3} & \mathbf{I}_{3\times3}\Delta t & \mathbf{0}_{3\times3} & \mathbf{0}_{3\times3} & \mathbf{0}_{3\times3} \\ \mathbf{0}_{3\times3} & \mathbf{I}_{3\times3} & \left[\bar{\mathbf{f}}^n \times\right]\Delta t & \mathbf{C}_b^n\Delta t & \mathbf{0}_{3\times3} \\ \mathbf{0}_{3\times3} & \mathbf{0}_{3\times3} & \mathbf{I}_{3\times3} & \mathbf{0}_{3\times3} & -\mathbf{C}_b^n\Delta t \\ \mathbf{0}_{3\times3} & \mathbf{0}_{3\times3} & \mathbf{0}_{3\times3} & \mathbf{I}_{3\times3} & \mathbf{0}_{3\times3} \\ \mathbf{0}_{3\times3} & \mathbf{0}_{3\times3} & \mathbf{0}_{3\times3} & \mathbf{0}_{3\times3} & \mathbf{I}_{3\times3} \end{bmatrix} \quad (12)$$

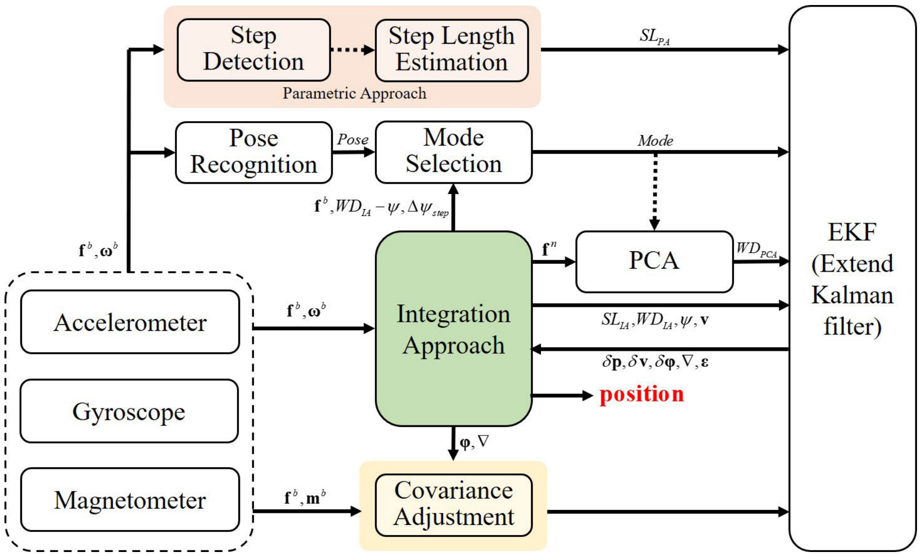


FIGURE 1. **Overall IA-PA fusion PDR algorithm.**

where $\mathbf{I}$ is the identity matrix and the numbers in subscript show its dimension. The zero matrix fit to dimensions is represented as $\mathbf{0}$ in the equation. In the proposed algorithm, the measurement updating processes are largely ZUPT, AHRS, and two-dimensional position from the PA. The first two processes are done in every sample, the other is every two steps.

B. MEASUREMENT MODEL

In case of ZUPT in the smartphone, the zero velocity phase rarely occurs, but it is performed in the initial alignment and stationary condition. The phase is detected using the windowed accelerometer z-axis variance, and the corresponding measurement equation is in (13) and (14).

$$\mathbf{z}_{ZUPT} = \mathbf{v}^n \tag{13}$$

$$\mathbf{H}_{ZUPT} = \begin{bmatrix} \mathbf{0}_{3\times3} & \mathbf{I}_{3\times3} & \mathbf{0}_{3\times3} & \mathbf{0}_{3\times3} & \mathbf{0}_{3\times3} \end{bmatrix}^T \tag{14}$$

Using accelerometer and magnetic measurements, attitude of the sensor is determined as follows.

$$\mathbf{z}_{AHRS} = \begin{bmatrix} \tilde{\mathbf{f}}^b - \tilde{\mathbf{C}}_n^b \mathbf{g}^n & \mathbf{y}_m^b - \tilde{\mathbf{C}}_n^b \mathbf{m}^n \end{bmatrix}^T \tag{15}$$

$$\mathbf{H}_{AHRS} = \begin{bmatrix} \mathbf{0}_{3\times3} & \mathbf{0}_{3\times3} & \tilde{\mathbf{C}}_n^b \left[\tilde{\mathbf{g}}^n \times\right] & \mathbf{I}_{3\times3} & \mathbf{0}_{3\times3} \\ \mathbf{0}_{3\times3} & \mathbf{0}_{3\times3} & \tilde{\mathbf{C}}_n^b \left[\tilde{\mathbf{m}}^n \times\right] & \mathbf{0}_{3\times3} & \mathbf{0}_{3\times3} \end{bmatrix} \tag{16}$$

The covariance is adjusted following the residuals using the ellipsoidal methods as described in section III-A3.

With the ZUPT and AHRS updates in the smartphone, the IA position is rapidly diverging. The PA position, however, is bounded because the step length is estimated from the parameters. Therefore, when the device heading and walking direction correspond to Fig. 2a, the 2D position calculated from PA is used as measurements. In situations such as Fig. 2a where the direction of walking matches the direction of the device, the PA position marked in orange can correct the IA position with the accumulated error indicated in green.

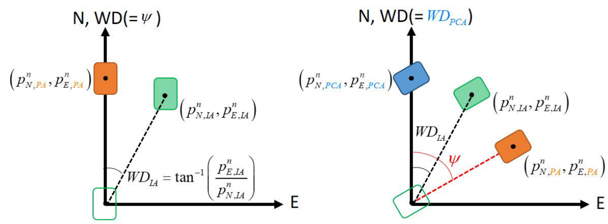


FIGURE 2. **Measurement update.**

As described in section III, the position from the PA-based PDR system consists of three major components: step detection, step length estimation, and heading estimation between two consecutive steps. With the estimated component, the position is calculated by (17).

$$\begin{bmatrix} p^n_{N,k} \\ p^n_{E,k} \end{bmatrix} = \begin{bmatrix} p^n_{N,k-1} + SL \cdot cos(\psi) \\ p^n_{E,k-1} + SL \cdot sin(\psi) \end{bmatrix} \tag{17}$$

where k is k-th step, $p^n_{N,k-1}, p^n_{E,k-1}$ is the previous position in north and east, respectively, and ψ is device heading.

In short, the measurement updates for PA positions are performed based on the heading match condition check. The heading difference between the walking direction calculated from two-step positions in IA and the device heading during two steps, and the classified pose are used for measurement mode decision. The reason for using a stride, two steps, is that the walking direction is oscillating following the walking characteristics of each user.

The walking direction and step length for IA are calculated as (18) and (19).

$$WD_{IA} = tan^{-1}\frac{\Delta p^n_E}{\Delta p^n_N} \tag{18}$$

$$SL_{IA} = \sqrt{(\Delta p_N^n)^2 + (\Delta p_E^n)^2} \tag{19}$$

where WD, Δp^n are walking direction and position between two steps, respectively.

For handheld conditions where the walking direction and device orientations match as shown in Fig. 2a, the heading offset is assumed as zero, so the step length from the PA and device heading are directly used to correct the IA states as in (20) and (20). In addition, assuming that the height for one stride are the same, the vertical position is also corrected.

$$\mathbf{z}_{match} = \begin{bmatrix} WD_{IA} - \psi & SL_{IA} - SL_{PA} & \Delta p_D^n \end{bmatrix}^T$$
$$\mathbf{H} = \begin{bmatrix} H_{11} & H_{12} & 0 & \mathbf{0}_{1\times 12} \\ H_{21} & H_{22} & 0 & \mathbf{0}_{1\times 12} \\ 0 & 0 & 1 & \mathbf{0}_{1\times 12} \end{bmatrix} \tag{20}$$

where

$$H_{11} = -\frac{\Delta p_{E,IA}^n}{(\Delta p_{N,IA}^n)^2 + (\Delta p_{E,IA}^n)^2}$$
$$H_{12} = \frac{\Delta p_{N,IA}^n}{(\Delta p_{N,IA}^n)^2 + (\Delta p_{E,IA}^n)^2}$$
$$H_{21} = \frac{\Delta p_{N,IA}^n}{\sqrt{(\Delta p_{N,IA}^n)^2 + (\Delta p_{E,IA}^n)^2}}$$
$$H_{22} = \frac{\Delta p_{E,IA}^n}{\sqrt{(\Delta p_{N,IA}^n)^2 + (\Delta p_{E,IA}^n)^2}} \tag{21}$$

The first component in (20) uses the heading angle to correct the course angle error calculated from the position. They have different stochastic characteristics, but the long-term characteristics are sufficiently similar that the difference can be neglected. Therefore, the above measurement can be used as above, since the course angle can be assumed to be dominated by the sensor heading error [53].

The problem in the PA position is that it only considers device heading not walking direction. If there are different poses such as putting the phone in the shirt or trouser pocket, the walking direction does not match with the device heading as Fig. 2b. In this case, there is a heading offset between walking direction and device heading. For the position from conventional PA shown in orange, errors are continuously generated because the position is estimated based on the device heading. However, in a mismatch situation, you can update the position of the IA in green through the position calculated by the PCA of the acceleration vector, this position marked blue in Fig. 2b.

As mentioned, for the mismatched heading case, the walking direction is calculated from the PCA. It is a technique that finds new bases orthogonal to each other while preserving the variance of data as much as possible and transforms samples from high-dimensional spaces into low-dimensional spaces without linear correlation [54], [55].

This approach takes advantage of the fact that the user's motion axis correlates with the largest variance axis in the horizontal acceleration that can be determined by PCA [31], [56]–[58]. The goal is to find the unit vector of walking direction, $\mathbf{u}_1$, which is the largest variance in the horizontal acceleration data $\mathbf{f}_m^n$ where $m = 1, \ldots, M$. Each data point $\mathbf{f}_m^n$ is projected on to a scalar value $\mathbf{u}_1^T\mathbf{f}_m^n$, and the mean of the projected data is $\mathbf{u}_1^T\bar{\mathbf{f}}^n$ where $\bar{\mathbf{f}}^n$ is sample set means represented as follows.

$$\bar{\mathbf{f}}^n = \frac{1}{M}\sum_{m=1}^{M}\mathbf{f}_m^n \tag{22}$$

There are various PCA-based methods such as PCA2D and PCA2Df to get the user's motion axis [31]. PCA2D is a PCA applied to the window on the 2D acceleration axis obtained by projecting onto the horizontal plane. The first eigenvector, which is the largest eigenvalue means a walking direction. Next, PCA2Df is almost same as PCA2D, but before applying PCA, the acceleration is low pass-filtered at 5 Hz to remove noise. According to [31] the 5 Hz average filter basically eliminates the body shaking noise, and it shows the best results in a series of tests that maintained the acceleration signal due to body movement. Since the PCA2Df is proved to be the most accurate in [31], so the walking direction is obtained from the PCA2Df in this paper. To address the 180-degree ambiguity inherent in the direction coming out of the PCA above, we adjust it with the direction through IA-based PDR.

Using the walking direction obtained from both IA and PCA, the IA states are updated as in (23).

$$\mathbf{z}_{mismatch} = \begin{bmatrix} WD_{IA} - WD_{PCA} & SL_{IA} - SL_{PA} & \Delta p_D^n \end{bmatrix}^T \tag{23}$$

V. EXPERIMENTAL RESULTS

A. PCA RESULTS

To check the performance of the walking direction calculated by the PCA, the dataset is generated in which scenario is a 25m round-trip linear trajectory, and the walking speed is 80, 90, 95, 100, and 105 beats per minute (BPM). The number of subjects participating in this experiment is 8 males and 4 females, a total of 12 subjects. Subjects are from 23 to 40 years of age with no physical disability. The sensor used is the Xsens MTw [59], [60]. Since this sensor can be wirelessly attached to multiple locations on the body and get synchronized data from all sensors. In this paper, the sensors are attached to the shirt pocket, hand, trouser pocket, and shoes as in Fig. 3. The sensor on the shoe is used to get an accurate heel strike point.

When the heel strike point is extracted from the shoe, the acceleration in the navigation frame during 1 stride, $\bar{\mathbf{f}}^n$, is calculated using the attitude provided by MTw. iRMPCA and PCA results from 12 subjects are shown in the Table 1. The results about 120 strides per person are checked, except for errors due to body movement and errors in the starting, ending, and in-situ rotation situations. Overall, the best results are when the device is in the pants pocket. This is because in the pocket, the sensor is fixed in the pocket and the output

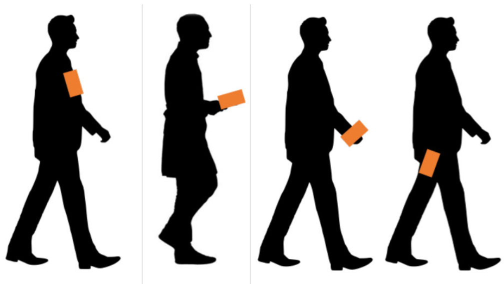


FIGURE 3. Target actions.

TABLE 1. Walking direction by PCA results.

error[deg]	Shirt		Trouser		Swing	
	iRMPCA	IA-PA	iRMPCA	IA-PA	iRMPCA	IA-PA
Mean	-1.15	-0.203	-0.234	0.025	0.115	-0.100
Std.	6.15	5.64	3.75	3.21	11.1	5.97
25% tile	1.96	1.16	0.814	0.706	3.60	1.29
Median	3.72	3.24	2.02	2.02	7.82	3.39
75% tile	7.48	6.37	3.74	3.65	13.7	7.00
95% tile	12.1	12.0	8.36	6.48	21.4	13.2

is completely caused by the movement of the leg, so it can indicate the direction of progress. On the other hand, the shirt pocket is fixed inside the pocket, but it seems that an error occurred because the upper body movement is relatively small. In the case of swing, the result is that the volatility is largely due to the movement of the hand having a large degree of freedom. In short, the result of the experiment shows that the walking direction from the PCA can be used as measurements. To compare iRMPCA and IA-PA, PCA method used in IA-PA is slightly more accurate, but the variance between those are pretty similar because both of those are based on the PCA methods.

B. IA-PA RESULTS

To compare and prove the performance of the IA and PA-based PDR system, the three trajectories are tested as Fig. 4. The first trajectory is a straight trajectory of 40m one way to check the results of the PCA under mismatch case, and the second trajectory is an L-shaped trajectory of 58m round trip to check whether the proposed algorithm works well even when rotation occurs in a pose other than text. The third trajectory is a square one of 194.6m to confirm if it is able to be operated for a long time. The Xsens Mtw sensor is mainly used and Galaxy Note9 is additionally used for trajectory 3. The sensor frame is defined the same as the body frame, which is forward, right, and down. The two conventional methods are used for the comparison. The first one is only PA-based position with (17) which uses the device heading. The other one is PCA-based position proposed in [36]. This method introduces a reference coordinate and performs PCA based on it, and it is called improved rotation matrix and PCA (iRMPCA) in this paper. There are other conventional methods, but those results using threshold-based or learning-based algorithms vary depending on the setting method, so it is excluded for the comparison. The position errors are calculated according to the known

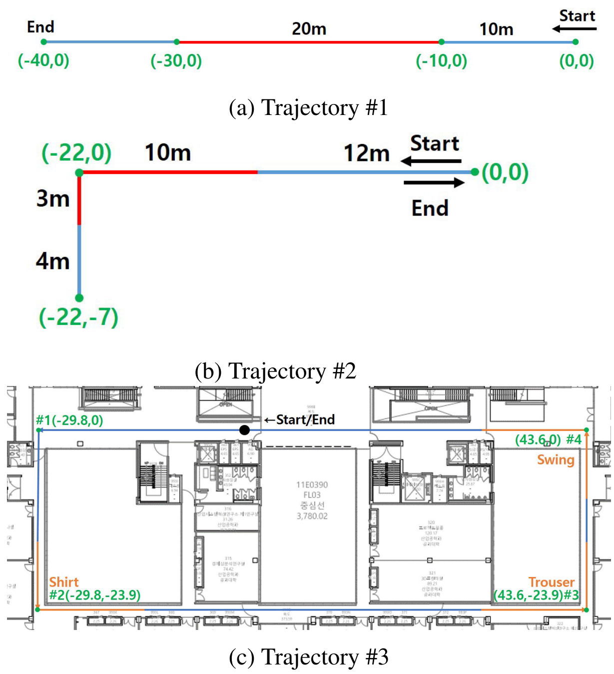


FIGURE 4. Trajectories (numbers in green represent way points in navigation frame).

way points' positions measured before the experiments, and then those are averaged for each method as the final position error.

Firstly, trajectory 1 is tested to check the feasibility of the proposed algorithm. It is tested whether the walking direction obtained by the PCA in the pose other than the text is correct. The following Fig. 5 and Table 2 the results of position estimation calculated for 10 subjects from the proposed algorithm. In Fig. 5, red, blue, and black indicate the proposed algorithm, iRMPCA, and PA-based algorithm, respectively. When the poses changed, it is marked with magenta, cyan, and gray, respectively. Through the proposed method, the problems that occur when the existing PA-based PDR estimation changes its poses can be solved. Compared to the iRMPCA, the proposed method also shows better results. In Table 2, the PA position results, in general, have large variances. It is because the results are dependent on the way how each tester performs those poses. The proposed method and the iRMPCA, on the other hand, calculate walking direction on the navigation frame and defined reference frame, respectively, so it is not less affected by the way how to do those poses as long as the attitude is estimated correctly. In the case of the iRMPCA, the defined reference frame is determined at the beginning while the user standstills. This could lead to the wrong estimation result when the reference frame is not correctly calculated. In addition, walking directions from iRMPCA vary following the way testers walk, especially in the trouser pocket and swing as shown in Table 2. In general, the proposed algorithm shows the most robust and accurate results because its positions are updated correctly through PA and PCA measurements.

TABLE 2. Position results for trajectory #1.

Pos. Error[m]	PA only		iRMPCA		IA-PA	
	Mean	Std.	Mean	Std.	Mean	Std.
Shirt Pocket	17.8	6.32	11.5	0.871	1.94	1.20
Trouser Pocket	12.6	4.61	10.1	2.89	1.67	1.03
Swing	8.76	4.86	5.54	3.26	1.79	1.28

Walking scenario 2 is a total of 58 meters of L-shaped round-trip track. The representative position and attitude estimation results for shirt poses are in Fig. 6. As seen from the position results in Fig. 6a, in the beginning, the results of PA and IA are the same during the text pose. The text pose is a situation in which the direction of movement is the same as the direction of the device, so the IA position is updated by the PA position. Therefore, the walking direction of IA calculated from the n-frame position and AHRS also correspond as in Fig. 6b. When the device is put on the shirt pocket, the position of PA is no longer corresponds to the walking direction, so the mode is changed into transition or mismatch in Fig. 6b. To explain each mode, mode 1 in Fig. 6b means ZUPT status. Mode 2 means the condition when walking direction and device attitude coincide, mode 3 means rotation or transition status, and mode 4 lastly means mismatch condition. Under mode 3 with the transition of poses or turning of the subject, and it shows a shorter step length than the regular walk between steps in Fig. 6a.

After the transition phase, the tester walks straight with the device put in the shirt, so the mode changes into the mismatch one. In Fig. 6b, it is noticeable that the device heading marked as WD_{PA} does not match with the walking direction represented as WD_{IA}. The error states are estimated following device attitude change in mode 4 through PCA-based measurement updates. This allows estimating correct positions of the proposed algorithm. When the device returns to the match mode, the position of the proposed method follows the characteristics of the PA. The iRMPCA is a step-based attitude, so it has a limitation to represent it for every sample. That is why it is omitted in Fig. 6b.

As seen from the results, the proposed algorithm is able to detect the device condition and estimate position by considering the heading difference between walking direction and heading. It is also noticeable that position errors are reduced using the proposed algorithm when the tester is rotating in place.

Similarly, when the device is placed in the trouser pocket or swing, the heading mismatch also occurs. When the sensor is placed in the trouser pocket, there are large attitude changes due to the repetitive leg movements. As we are using the mean heading of two consecutive steps, the swaying heading angle from the leg does not affect the position results.

Lastly, the trajectory with the only handheld case is tested as in Fig. 7. The iRMPCA with text poses show the same results, so it is not represented in the figure. As seen from the figure, the proposed algorithm is also advantageous even in the handheld case during rotating in place. The conventional PA algorithm calculates the step length only based on the walking frequency, so errors occur in sections with short strides, such as rotating in place. The proposed algorithm detects the turning phase and calculates the step length from the IA, which is more accurate than the PA method.

The position results in Fig. 7, however, could lead to one of the limitations of the proposed algorithm that the IA results

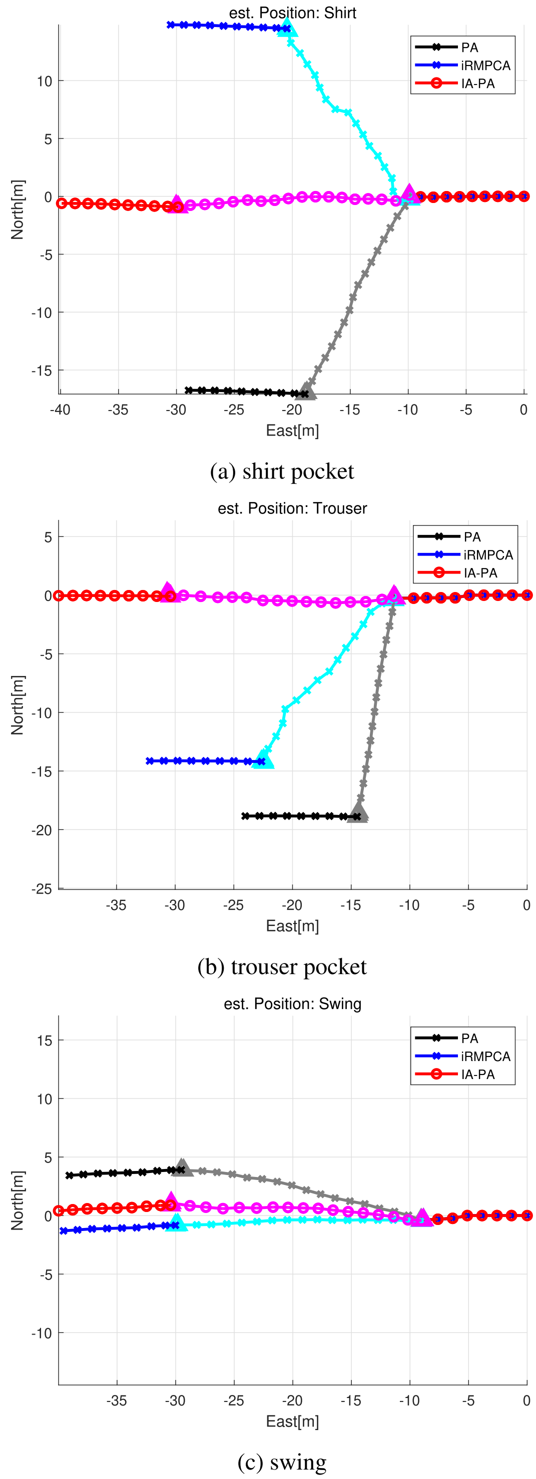
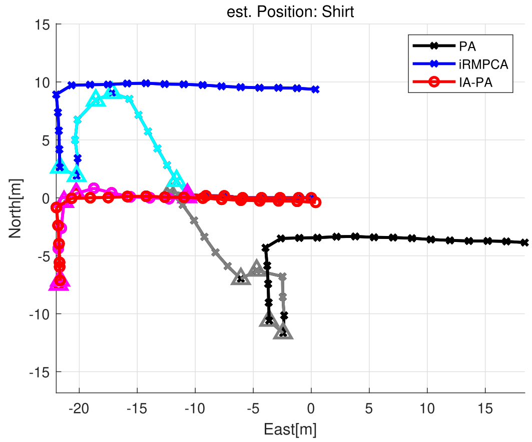
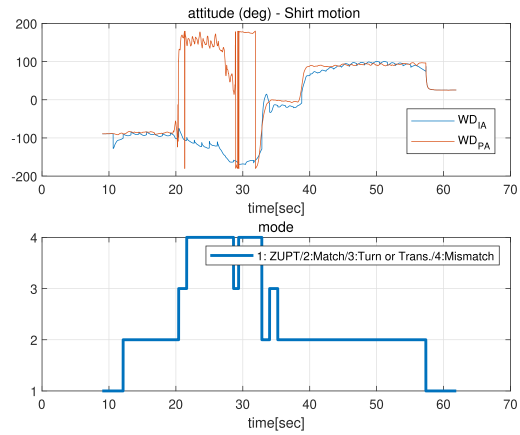


FIGURE 5. Estimated position.



(a) Position



(b) Attitude and mode

FIGURE 6. Position and attitude results for shirt pocket pose.

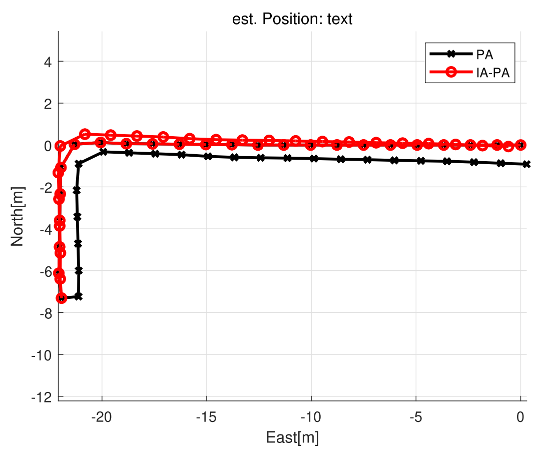


FIGURE 7. Position result for text only pose.

follow the PA features. To be specific, the step length and heading of the device are incorrect; the measurement updates of those lead to position errors. Therefore, the correct step length and device attitude estimation of PA is the prerequisites of the proposed algorithm.

TABLE 3. Position results for trajectory #2.

RPE [m]	PA only	iRMPCA	IA-PA
Shirt pocket	12.1	9.44	1.65
Trouser pocket	8.02	6.24	2.04
Swing	3.94	2.22	1.61
Text only	0.97	0.97	0.43

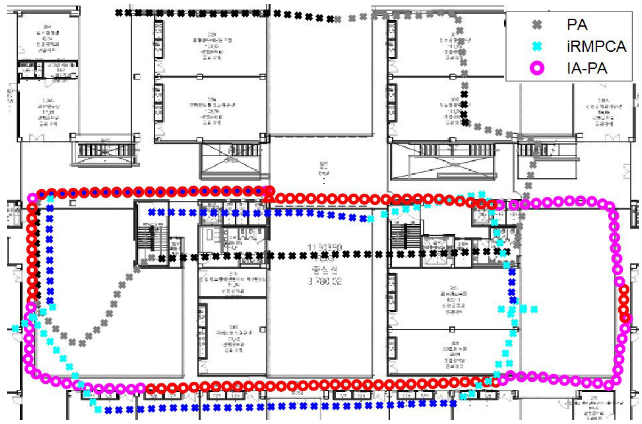


FIGURE 8. Position result for trajectory #3.

The position results of trajectory 2 are in Table 3. The above results show that the algorithm can be applied in other situations wherever there is a heading mismatch.

Trajectory 3 is performed to see that the proposed algorithm works well even on the long trajectory, and the trajectory is a rectangular-shape of 194.6m performed at Building 39 in Seoul National University, Republic of Korea. The result of the proposed algorithm is shown in Fig. 8. In the case of position error, it is calculated based on four waypoints in every corner and the returned position, and the proposed algorithm has a position error of **2.13m**, PA of **20.01m**, and iRMPCA of **10.48m** for the Xsens MTw sensor, and averaged error in 5 repeated times of **2.49m**, **23.14m**, and **12.35m** respectively for Galaxy Note9 device. This shows that even after walking for a long time, the proposed algorithm yields good results.

We would like to mention that the proposed algorithm has some limitations to be improved. The proposed IA-PA PDR fusion algorithm is dependent on the step length estimation performance of the PA. In the proposed algorithm, the step length from the PA is assumed to be accurate, so the position of the IA is limited to the accuracy of the PA position. If there is a small angle difference between walking direction and device heading during text message pose, the proposed algorithm just follows the attitude of the device. In addition, it is reasonable to use the walking direction obtained from the PCA as a measurement, but it is better to further adjust the heading using other information such as the dominant direction and multiple virtual tracks. This helps in updating the wrong measurements due to errors in the PCA. In addition, external location information such as Wi-Fi and map information can be used to adjust for accumulated location errors. As mentioned earlier, the accuracy of the proposed algorithm is limited to one of the PA-based step lengths. This means that accumulated step length errors are inevitable. Therefore, the external position source helps in scaling the step length parameters.

VI. CONCLUSION

In this paper, we propose the PDR system with the fusion of the IA and PA for robust smartphone position estimation. The algorithm is proposed in order to avoid severe position errors from the difference between the walking direction and the device heading. The fusion algorithm estimates the position from the IA-based PDR system, with the measurement of step length from the PA and device heading under the correspondence mode. If the walking direction and the device heading do not match during the pose other than text, the position is updated in consideration of the direction calculated using PCA and the step length obtained through the PA. The proposed algorithm shows its effectiveness in the experiments that position is correctly estimated under shirt pocket, text, swinging, and trouser pocket poses.

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