JPNT 11(1), 35-44 (2022)
https://doi.org/10.11003/JPNT.2022.11.1.35

JPNT Journal of Positioning, Navigation, and Timing

Dual Foot-PDR System Considering Lateral Position Error Characteristics

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ABSTRACT

In this paper, a dual foot (DF)-PDR system is proposed for the fusion of integration (IA)-based PDR systems independently applied on both shoes. The horizontal positions of the two shoes estimated from each PDR system are fused based on a particle filter. The proposed method bounds the position error even if the walking time increases without an additional sensor. The distribution of particles is a non-Gaussian distribution to express the lateral error due to systematic drift. Assuming that the shoe position is the pedestrian position, the multi-modal position distribution can be fused into one using the Gaussian sum. The fused pedestrian position is used as a measurement of each particle filter so that the position error is corrected. As a result, experimental results show that position of pedestrians can be effectively estimated by using only the inertial sensors attached to both shoes.

Keywords: pedestrian dead reckoning, integration approach, dual foot-mounted inertial sensors, indoor pedestrian navigation

1. INTRODUCTION

A personal navigation system (PNS), which provides a user's position to a special agent such as a firefighter or soldier, is recognized as an important technology for their safety and mission success. Among the methods of estimating the position, the Global Navigation Satellite System (GNSS) provides position information in various environments (Wang et al. 2012). But, this method is unsuitable for agents who perform missions indoors or outdoors because position estimation accuracy using GNSS is degraded by the blocking or distortion of satellite signals. An alternative method can be classified according to whether wireless equipment is used. A position estimation method estimates the user position using radio signals from wireless infrastructure such as Wi-Fi and BLE (Cho 2016). Since this method can only be used where the wireless infrastructure is already installed, the availability problem depending on the location, such as GNSS, is a disadvantage.

On the other hand, pedestrian dead reckoning (PDR), which uses IMU built into the user device or attached to the body, has the advantage of being available regardless of the place where it is used. PDR is a method of estimating the pedestrian position by considering the walking characteristic included in the acceleration and angular velocity data measured by the IMU. This method is classified into a parametric approach (PA) that detects steps and adds estimated step length in the direction of movement (Kim et al. 2004, Shin & Park 2011), and an integration approach (IA) that integrates the inertial sensor output according to the inertial navigation system (INS) mechanization (Foxlin 2005, Ju & Park 2018). The PA-based PDR system enables stable step detection through various techniques, but to determine the correct walking direction, the gait type must be accurately recognized. On the other hand, the IA-based PDR system does not require gait type recognition, but the navigation accuracy calculated by the INS mechanism

Received Feb 23, 2022 **Revised** Mar 03, 2022 **Accepted** Mar 04, 2022
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http://www.ipnt.or.kr Print ISSN: 2288-8187 Online ISSN: 2289-0866

rapidly decreases over time. To solve this problem, an IA-based PDR system is usually used an IMU attached to a shoe, and it must detect the zero-velocity at which the shoe touches the ground and perform ZUPT to correct the error. This system is designed based on an extended Kalman filter (EKF) in consideration of the nonlinearity of INS. It provides high position estimation accuracy and we demonstrated this through the IPIN 2016 competition. But it cannot estimate position error and heading errors in filters that use only zero-velocity measurements. To compensate for this, various studies are conducted to correct the position error using prior building information such as map information or corridor direction (Borenstein & Ojeda 2010).

However, these methods also have constraints that preliminary preparations such as map information are required for firefighters to be put into various environments. There are also studies in which inertial sensors are attached to both shoes and fused to correct the position error with only inertial sensors without additional information or equipment. One of the methods is limiting the stride range of each shoe's estimated position (Shi et al. 2017, Zhao et al. 2019). When this method is applied, the position accuracy is improved instead of using a standalone PDR system. However, since this method only corrects position errors larger than the range limit, there is a disadvantage that the error within the range cannot be corrected. Another method is to use an ultrasonic sensor to correct the position of both shoes (Weenk et al. 2015). However, this has the difference that it requires an additional sensor, unlike the previous research using only the IMU.

In this paper, we propose a dual foot (DF)-PDR system that fuses the estimated lateral position of shoes from each PDR system using a particle filter (PF). The position error, estimated by the PDR system using the IMU mounted on each shoe, shows a systematic drift characteristic, which means the shoe's symmetrical position error in the lateral direction (Nilsson et al. 2013). The horizontal position is separated from the states of the EKF constituting the IA-based PDR, and the horizontal position is defined as the states of the particle filter. Using the particle filter is suitable to express the position error caused by systematic drift. The estimated shoe position in each particle filter is fused using the Gaussian mixing method and expressed as the pedestrian position. The fused pedestrian position is used as a measurement of the particle filter to correct the position error.

This paper is organized as follows. After presenting the experimental and analysis results for systematic drift, which is the basis for applying the DF-PDR system, in Section 2, a detailed description of the proposed system is described in Section 3. In Section 4, we verify the performance of the proposed method through actual walking experiments and the results, and we conclude this paper in Section 5.

2. ERROR CHARACTERISTICS OF STANDALONE PDR SYSTEM

2.1 Systematic Drift in Standalone PDR System

The systematic drift of the IA-based PDR system means that the error of the estimated position in the PDR system of both shoes drifts symmetrically in the lateral direction. This error is called systematic drift or symmetric drift (Nilsson et al. 2012) and becomes a basic assumption for improving the accuracy of estimated pedestrian position through the fusion of both shoe positions in the DF-PDR system. Various research results using systematic drift have been proposed, but a definite cause analysis for this phenomenon has not been conducted properly. Most of the papers mention only the systematic drift results in the position domain (Nilsson et al. 2013, Shi et al. 2017). Before proposing the fusion method, we try to find the cause of the error.

Systematic drift can be observed when walking on a straight trajectory. The experimenter walked 20 times along a 70 m straight trajectory. IMUs were attached to each of the two shoes, and the position of the shoes was estimated using an IA-based PDR system consisting of EKF and zero-velocity update (ZUPT). The coordinate system is the Local Level Coordinate System, and the initial movement direction is defined by the X-axis and the lateral direction by the Y-axis. Standing still for 10 seconds before walking, we estimated and eliminated the gyro bias of each IMU to minimize position errors due to gyro bias. Also, the shoe's initial direction and the walking direction were matched using the estimated position during the initial five steps.

Fig. 1a is the average of the estimated shoe position in the 20 experiments. The blue and red trajectories are the results of the left and right shoes' estimated position, respectively. Pedestrians walked on a straight trajectory, so if there is no position error, the two trajectories should be straight parallel to the X-axis. However, it is observed that the estimated position error drifts in the negative direction of the Y-axis for the left shoe and the positive direction for the right shoe. Fig. 1b shows the estimated position at the last step in each test. As in (a), it can be seen that the positions of the left and right shoes are divided and distributed based on the X-axis. This is a systematic drift phenomenon, and the drift refers to the tendency of position errors to occur in opposite directions based on the moving direction.

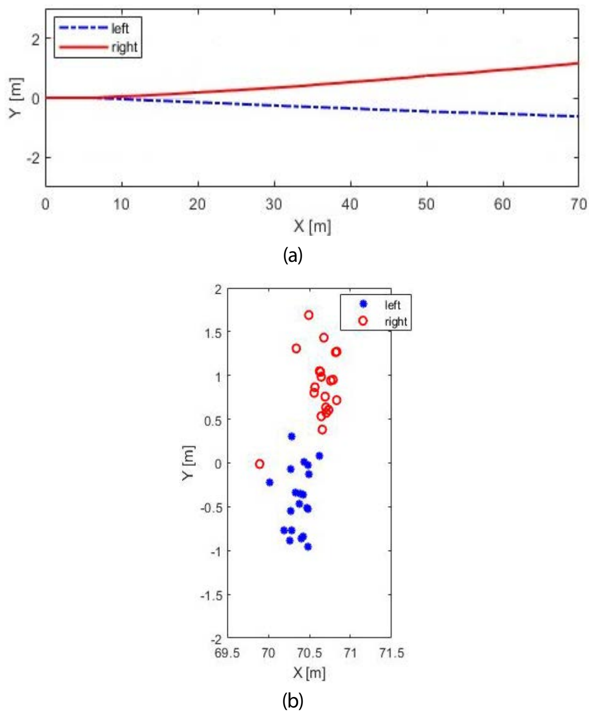

Fig. 1. Experimental results with each shoe. (a) average of estimated position with each shoe, (b) estimated positions at last step.

There are also existing studies that analyzed the causes of such systematic drift. Considering previous studies that analyzed the cause of systematic drift, it can be inferred that the IMU sampling frequency is one of the causes of drift (Lee et al. 2020). In this study, to verify the relationship between the sampling frequency of the IMU and the systematic dritf, the sampling frequency was set to 1,000 Hz and used as a reference value. Downsampling was performed to produce an IMU output with a frequency lower than 1,000 Hz. Using this, they compared and analyzed how the estimated position, speed, and posture differ from the reference values. According to the results of this paper, yaw and lateral velocity errors occur due to low sampling frequency, and this has a symmetrical characteristic.

2.2 Distribution of Position Error by Systematic Drift

IA-based PDR systems can be designed using various filters. In general, in IA-based PDR systems that estimate the position through the INS mechanism, EKF is used to consider the nonlinearity of the INS. EKF is a filter that gives good estimation performance in a PDR system, but it is only suitable if the error can be expressed as a Gaussian distribution. In the PDR system, the process noise of EKF is assumed to be the Gaussian distribution of acceleration and angular velocity. However, since the position error called

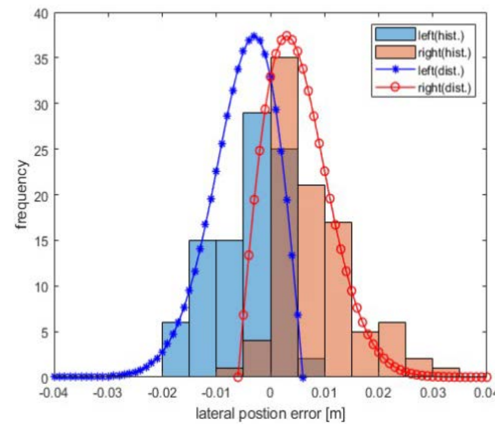

Fig. 2. Distribution of the lateral position error in one step.

systematic drift can be seen in the previous chapter, it must be considered in the filter to improve position estimation performance. We tried to check whether the distribution of position errors in the lateral direction is suitable for EKF through 100 experiments. Fig. 2 shows the histogram results of the lateral position error for the left and right shoes. The histogram of the right shoe's position can be observed that the shape of the distribution is asymmetric, and the mode of the distribution is skewed from the center to the left. Conversely, the histogram of the left shoe position is the same as the right one that is asymmetric, and the mode is skewed from the center to the right. Various distributions can express asymmetry distribution, but we try to express the position error by modifying the Rayleigh distribution in the proposed method. The subset of the domain containing the elements of the Rayleigh distribution must be zero or more. However, since the position error should not be defined only in the positive domain, the Rayleigh distribution expressed in the positive domain was offset so that the negative domain could also be expressed.

$$f(x;\sigma)=\frac{x}{\sigma^2}e^{-x^2/(2\sigma^2)},\ x\geq 0 \tag{1}$$

Eq. (1) represents the Rayleigh distribution. is a subset of the domain, and when used in the proposed method, it is offset in the negative direction. Also, the left position error distribution flips the distribution of the right shoe's position error so that the modes are skewed in opposite directions. Since the Gaussian distribution is a representative distribution with a symmetrical shape, it is not suitable to express the position error observed earlier. The modified Rayleigh distribution is drawn in Fig. 2, and it is the result of growing it to match the histogram.

Since the proposed position error distribution is not Gaussian distribution, it violates the conditions for applying

Algorithm 1

Time update of Kalman filter and particle filter:
for $i \in \{r, l\}$
$\hat{x}^i_{EKF,k} \leftarrow x^i_{EKF,k-1}$ $\{INS\ mechanism\}$
$P^i_k \leftarrow F^i_k P^i_{k-1} F^{iT}_k + Q^i_k$
for $n = 1, \ldots, N$
$x^{i,(n)}_{PF,k} \sim P(x^i_{PF,k} \mid x^i_{PF,k-1}, u_k)$ $\{predict\ new\ particle\}$
end
end

Extended Kalman filter measurement update at each PDR system:
if *shoe i is zero velocity*
update $\hat{x}^i_{EKF,k}, P^i_k$ *by zupt*
end

Particle filter measurement update:
$z_k \leftarrow Gaussian\ mixture\{\hat{x}^l_{PF}, x^r_{PF}\}$
for $n = 1, \ldots, N$
$q^{i,(n)}_k = p(z_k \mid \hat{x}^i_{PF,k}, z_{k-1})$ $\{importance\ weights\}$
end
$\{resample\ N\ particles\ with\ q^i_k\}$

EKF. Therefore, the proposed method uses a particle filter to estimate the position using the proposed position error distribution. Particle filters are not well used in PDR systems because of their large computational volume, so only horizontal positions were estimated using a particle filter, and velocity and attitude errors were estimated using EKF.

3. PARTICLE FILTER DF-PDR SYSTEM

The system's structure proposed in this paper uses two filters to estimate each state estimated in a general PDR system separately. In this case, the particle filter uses the result estimated from EKF, which is similar to a marginalized particle filter (Schon et al. 2005). Algorithm 1 is an overview of the proposed method. Time update and measurement update of EKF are performed independently in each PDR system, and measurement update of the particle filter is performed by receiving information from the opposite side PDR system.

After obtaining the value of the measurement (u) from the IMU, the attitude and velocity are calculated according to the INS mechanization (Section 3.1). Each PDR system uses EKF to update the covariance for the state variable, and in the zero-velocity phase, ZUPT is used to estimate and correct the state related to EKF (Section 3.1). Since the EKF does not estimate the horizontal position but through a particle filter, the particles representing the horizontal position are propagated together in the time propagation step of the EKF (Section 3.2). Filters that estimate each shoe state are independently executed until the positions of the shoes are fused. The position from the PDR system that estimates each shoe's position is fused by a Gaussian mixture method to indicate the position of the pedestrian. Regardless of the left and right, at the end of the zero-velocity phase, the fused pedestrian position is used for the measurement update of the particle filter (Section 3.2). Fig. 3 is an overall diagram of the system, and the structure of the right PDR system is the same as that of the left PDR system.

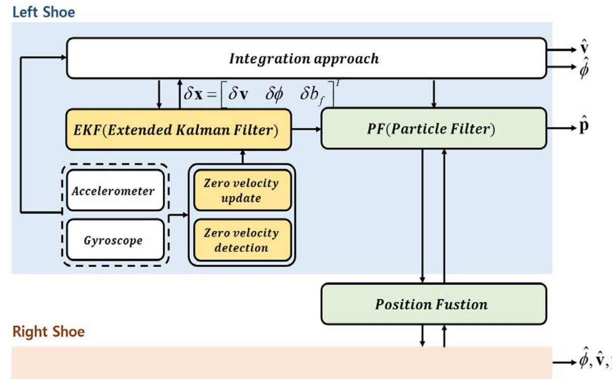

Fig. 3. Overall diagram of proposed method.

3.1 IA-based PDR System in Each Shoe

Since the proposed method is similar to the marginalized particle filter structure, the state updated by PF and the state updated by EKF is divided and defined as follow

$$\mathbf{x} = \left[\mathbf{x}^T_{PF} \quad \mathbf{x}^T_{EKF} \right]^T \tag{2}$$

$\mathbf{x}_{PF}$ is the state in the particle filter and consists of the horizontal position p_X and p_Y. EKF estimates the remaining state variables. In EKF, error state variables are defined and estimated. The error state variables for EKF are as follows.

$$\delta\mathbf{x}_{EKF} = \left[\delta p_Z \quad (\delta\mathbf{v}^l)^T \quad (\delta\phi^l)^T \quad (\delta\nabla^b)^T \right]^T \tag{3}$$

δp_Z is the vertical axis position error, δv^l is the velocity error in the local horizontal coordinate system $\{l\}$, $\delta\phi^l$ is the attitude error about the horizontal axis, and $\delta\nabla^b$ is the acceleration bias error in the body frame $\{b\}$. By measurement update through ZUPT, heading error and gyro bias are not well estimated as the unobservable state, so in the proposed method, these variables were excluded from the state variable. The gyro bias was estimated and compensated for by averaging the gyro signal while standing still before walking.

Time propagation of navigation information is done through the INS mechanism. Since the inertial sensor mainly used in the PDR system is low-cost, the INS mechanism can be simplified by ignoring Earth's rotation and Coriolis force due to error characteristics and relatively low sampling frequency.

$$\begin{aligned} \dot{q} &= \frac{1}{2}\grave{\mathrm{U}}(\omega)\otimes q, \\ \dot{\mathbf{v}}^l &= C_b^l f^b - \mathbf{g}^l \\ \dot{\mathbf{p}}^l &= \mathbf{v}^l \end{aligned} \tag{4}$$

q is quaternion to representing rotation from frame $\{b\}$ to frame $\{l\}$. $\mathbf{g}^l$ is gravity vector. f^b and are the acceleration and angular velocity measured by the inertial sensor,

$$\mathbf{\Omega}(\omega) = \begin{bmatrix} -\omega\times & \omega \\ -\omega^T & 0 \end{bmatrix}, \ \omega\times = \begin{bmatrix} 0 & -\omega_z & \omega_y \\ \omega_z & 0 & -\omega_x \\ -\omega_y & \omega_x & 0 \end{bmatrix}.$$

The IA-based PDR system is a PDR system that is generally performed by attaching an IMU to a shoe. This system calculates the navigation solution using the INS mechanism. Therefore, navigation errors increase over time due to error factors such as bias. To compensate for the error, zero-velocity is detected in the stance phase when the shoe touches the ground, and the error of the state is estimated and compensated by performing ZUPT.

The proposed method first estimates the error state vector, $\delta\mathbf{x}_{EKF}$, using EKF. The discrete state-space model can be expressed as follows.

$$\begin{aligned} \delta\mathbf{x}_{EKF,k|k-1} &= \Phi_k \delta\mathbf{x}_{EKF,k-1|k-1} + w_k \\ \mathbf{z}_k &= \mathbf{H}\mathbf{x}_{EKF,k|k-1} + \eta_k \end{aligned} \tag{5}$$

where k is a timestamp, Φ_k is state transition matrix, and $\mathbf{H}$ is measurement matrix. w and η mean process noise and measurement noise.

The state transition matrix can be expressed as follows through the error model of Eq. (4).

$$\Phi_k = \begin{bmatrix} 1 & \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} dt & \mathbf{0}_{1\times2} & \mathbf{0}_{3\times3} \\ 0 & \mathbf{I}_{3\times3} & [f^n\times]_{3\times2}dt & C_b^n dt \\ 0 & \mathbf{0}_{2\times3} & \mathbf{I}_{2\times2} & \mathbf{0}_{2\times3} \\ 0 & \mathbf{0}_{3\times3} & \mathbf{0}_{3\times2} & \mathbf{I}_{3\times3} \end{bmatrix} \tag{6}$$

where $\mathbf{I}$ is the identity matrix, and subscribe means the dimension of the matrix. $[f^n\times]_{3\times2}$ is a matrix without 3rd column in $[f^n\times]$. dt is a time difference between sequential two samples.

The zero-velocity means when the shoe touches the ground and does not move, and the stationary state can be detected through the inertial sensor output value. The detection was configured by referring to Lee et al. (2012). The matrix of measurements of the zero-velocity correction is as follows.

$$\mathbf{H} \quad [\quad \mathbf{I}_{3\times3} \quad \mathbf{0}_{3\times2} \quad \mathbf{0}_{3\times3}] \tag{7}$$

3.2 Particle Filter for Horizontal Position Update

The horizontal position is excluded from the error state of EKF described in Section 3.2. In the proposed method, the horizontal position is time propagation and measurement update using a particle filter.

When the relationship of the state variable defined in Eq. (2) is expressed as a probability, it can be expressed as follows by Bayes' theorem.

$$p(\mathbf{x}_k \mid \mathbf{z}_k) = p(\mathbf{x}_{PF,k} \mid \mathbf{x}_{EKF}, \mathbf{z}_k)\, p(\mathbf{x}_{EKF} \mid \mathbf{z}_k) \tag{8}$$

As shown in Eq. (8), the posterior can be divided into position and probability of other state variables, which means that each state variable can be updated with a different filter. The probability distribution for the location is

$$\mathbf{x}_{PF,k}^{(n)} \sim p(\mathbf{x}_{PF,k}^{(n)} \mid \mathbf{x}_{PF,k-1}, \mathbf{x}_{EKF,k}, \mathbf{z}_{k-1}) \tag{9}$$

where n is the index for N particles. In a particle filter, the state is updated through the time propagation of particles. Referring to Eq. (4), the particle for the position is updated from the velocity probability. At this time, the probability distribution of the velocity can be obtained from the error covariance of EKF.

If only the error covariance of the velocity is considered, it becomes propagation with the same probability distribution as the existing EKF. For error in horizontal position due to systematic drift, the probability distribution of drift must be additionally considered in the propagation of particle filter. Section 2 showed that the lateral position error showed an asymmetric distribution, not a Gaussian distribution. The proposed method propagates particles using Rayleigh distribution based on this.

For propagation of particles, the prior is determined based on Eq. (10).

$$\mathbf{x}_{PF,k} \sim N(\mathbf{x}_{PF,k-1}, \mathbf{P}_{pos.k}) + \begin{bmatrix} x_{N,sys} \\ x_{E,sys} \end{bmatrix} \tag{10}$$

The first term is that expresses the error of the position

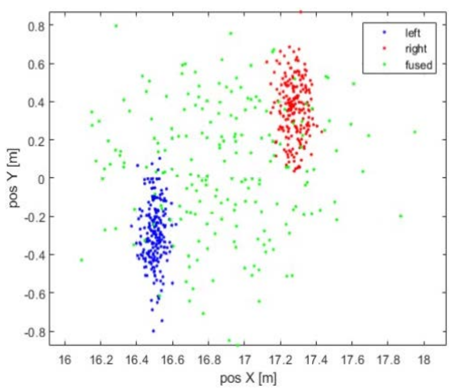

Fig. 4. Fused position represents the pedestrian's center.

Fig. 5. Location of the inertial sensors.

Table 1. Specification of MTw.

	Gyro	Accelerometer
Dynamic range	$\pm 1200\,deg/s$	$\pm 160\,m/s^2$
Bias stability	$20\,deg/hr$	-
Noise	$0.05\,deg/s/\sqrt{Hz}$	$0.003\,m/s^2/\sqrt{Hz}$

from the velocity covariance of the EKF. It is defined by Eq. (11).

$$\mathbf{P}_{pos.k} = \mathbf{P}_{vel} \cdot dt^2 \tag{11}$$

The second term of Eq. (10) is the probability distribution considering systematic drift. Position error occurs only in the lateral direction, which is defined in frame {b}. However, the domain of the particle is frame {l}, so frame conversion is required.

$$\begin{bmatrix} x_{N,sys} \\ x_{E,sys} \end{bmatrix} \sim C_b^n \begin{bmatrix} 0 & 0 \\ 0 & f'(\mathbf{x}_{PF,k-1}^b; \sigma_{sys}) \end{bmatrix} \tag{12}$$

f' is the offset Rayleigh distribution and σ_{sys} is a parameter expressing the lateral position error.

The position estimated by each independent PDR system means the shoe's position, but the position estimated by the two shoes should be similar in terms of ultimately estimating the position of a pedestrian. In other words, the estimated shoe position in each shoe can be assumed as two measures of pedestrian position. The estimated position in each PDR system represents the position of a pedestrian in a multi-modal form. The distribution of fused position, p^{fused}, is obtained using the Gaussian sum method to represent a single position distribution for pedestrians. a Gaussian sum of the form represents the fused position.

$$p^{fused} = \sum_n \alpha^{(n)} N(p^i \mid \mu^i, \Sigma^i) \tag{13}$$

$$\mu^i = \frac{1}{N}\sum_n p^{i,(n)},\ \Sigma^i = \frac{1}{N}\sum_n (p^{i,(n)} - \mu^i)^2 \tag{14}$$

where α is the weight for each particle, μ^i and Σ^i are the mean and covariance representing each shoe's measured position, and N is the number of particles. Fig. 4 shows the distribution of each system's particles and the distribution of the fused position at a time point when the proposed algorithm is applied. The number of particles in the system was set to 100. Since the distribution of particles estimated by each PDR system considers systematic drift, it can be confirmed that it is more widely distributed in the lateral direction. The result of fused particles of the two systems is green. It can be seen that it includes positions of both systems, and the center of the distribution is positioned in the center relative to the side without being skewed anywhere on the left and right.

The fused position obtained in this way becomes the position measurement of each system and is used to measure the particle filter. The likelihood for the update can be computed as follows:

$$L(\mathbf{z}_k \mid \mathbf{x}_k) \sim N(p^{fused} \mid \mu^i, \Sigma^i) \tag{15}$$

Since the center of the position distribution fused by the Gaussian mixture is in the middle of both feet, the horizontal position that should diverge due to systematic drift does not diverge.

$$p(\mathbf{x}_{PF,k} \mid \mathbf{z}_k) \propto L(\mathbf{z}_k \mid \mathbf{x}_k) p(\mathbf{x}_{PF,k} \mid \mathbf{x}_{k-1}, \mathbf{z}_{k-1}) \tag{16}$$

Eq. (16) is the relationship between the posterior probability of the 2D position and the likelihood and prior probability according to the Bayes' rule. The importance weights for each particle were calculated by likelihood, considering the fused probability of positions, and resampling was performed. Resampling must be performed to manage high-quality particles, and in the proposed method, a systematic resampling technique that divides particles with large weights was used (Kitagawa 1996).

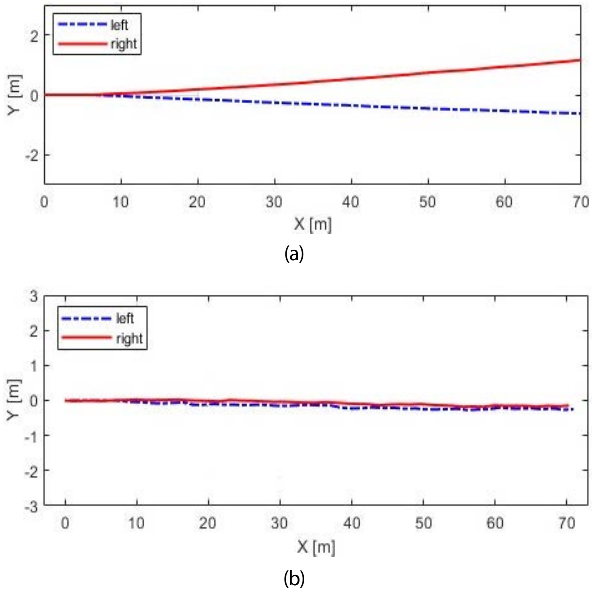

Fig. 6. Estimated position using each algorithm (straight trajectory). (a) standalone PDR. (b) proposed DF-PDR system.

Table 2. Error of estimated position (Straight).

	Left		Right	
	Mean	Std.	Mean	Std.
Standalone	0.52	0.32	0.97	0.33
Range constraint	**0.40**	0.23	0.82	0.21
Proposed	0.48	**0.13**	**0.55**	**0.18**

4. EXPERIMENT RESULTS

To verify the performance of the proposed DF-PDR system, a walking experiment was performed. As shown in Fig. 5, Xsens' IMU, MTw, was attached to the outside of each shoe. The sensor can be attached in various ways, but it is set to the rear side in this paper. The sensor performance is summarized in Table 1. Acceleration and angular velocity from IMU were acquired at 100 Hz.

There are two types of walking trajectories, straight and square. The performance of the proposed method was analyzed through the results of estimating the position of pedestrians using the independent IA-based PDR system without location fusion and the proposed DF-PDR system. The linear trajectory was performed 20 times, and the square trajectory was performed three times each for left and right rotation, and a total of six data were obtained for each trajectory, and the gyro bias was corrected using the data obtained by standing still about 5 seconds before walking. To compare the performance difference between the previous method and the proposed method, the range constraint method was implemented by referring to Prateek et al. (2013). This method defines the maximum step length

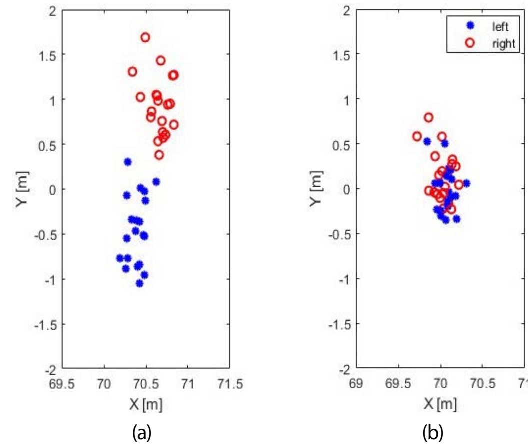

Fig. 7. Estimated positions at last step shoe. (a) standalone PDR. (b) proposed DF-PDR system.

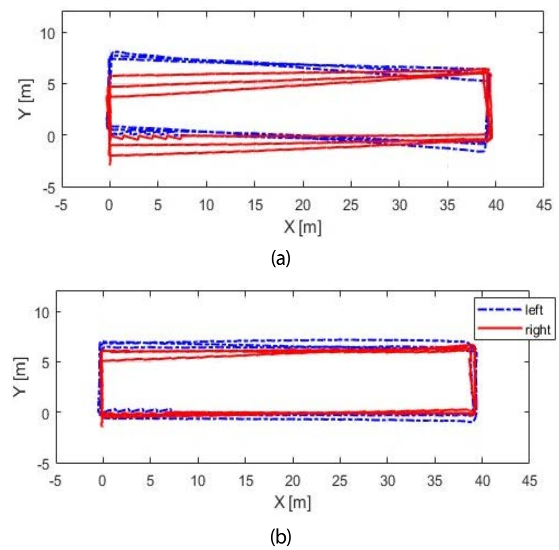

Fig. 8. Estimated position using each algorithm (square trajectory). (a) standalone PDR. (b) proposed DF-PDR system.

and corrects the position inside the range constraint if there is a position error beyond that.

In a straight trajectory, the position error's mean was calculated for the final position. Fig. 6 shows the estimated position when each PDR is used independently and when two PDRs are fused, and the position error of the two PDRs is corrected based on this. This is a result showing only one of several experiments. If standalone PDR is used as in (a), it can be seen that the position estimation error gradually increases toward the side in the forward direction. On the other hand, in the case of using the proposed method, it can be seen that the lateral position estimation error is reduced. In Table 2, the proposed method's average position error was 0.48 m and 0.55 m, respectively, while the average position error of the standalone PDR was 0.52 m for the left

Table 3. Error of estimated position (Square).

	Left		Right	
	Mean	Std.	Mean	Std.
Standalone	0.50	0.55	1.28	1.46
Range constraint	0.46	0.61	0.40	0.68
Proposed	**0.32**	**0.53**	**0.31**	**0.54**

Table 4. Error of estimated position (Long).

	Left		Right	
	Mean	Std.	Mean	Std.
Proposed	1.58	0.97	1.53	1.01

foot and 0.97 m for the right foot. Although it does not seem to be significantly improved numerically, it can be seen that the estimation performance improved from 0.32 to 0.13 by comparing the standard deviation. It can also be seen in Fig. 7, which shows the position estimate for the last step. If the proposed method is used, the position distributed around different centers on the X-axis are distributed based on 0, and it can be seen that the variance is reduced. In Table 2, the previous method using range constraints outperforms the standalone method, but the positional error is larger than the proposed method. Although estimating the left shoe position is better than the proposed method, the difference is not significant, and the standard deviation is smaller in the proposed method.

In the standalone PDR, the position error of pedestrians walking 70 m was an average of 0.5 m. This is similar to a person's stride. If a correction technique considering only the boundary for stride is used in the DF-PDR system, the error cannot be corrected at a moving distance of 70 m or less. On the other hand, since the proposed algorithm fuses the position without conditions, it reduces the lateral error and improves the position accuracy.

In the second experiment, the experimenter returned to the initial position after three turns along the square trajectory. The circumference of the square is about 93 m, and the experimenter walked for 3 minutes. Fig. 8 and Table 3 show the performance results of both techniques. In Fig. 8, it can be seen that the position estimated by the standalone PDR deviates from the reference trajectory as if rotating. This is a result affected by systematic drift. On the other hand, in the case of using the proposed method, it can be confirmed that the estimated position is estimated to fit the reference trajectory because the lateral direction error is corrected like the linear trajectory. The average position error for the waypoint was also improved compared to the standalone PDR. This test result verified that the proposed DF-PDR system could accurately estimate the position of pedestrians with only an inertial sensor module without additional

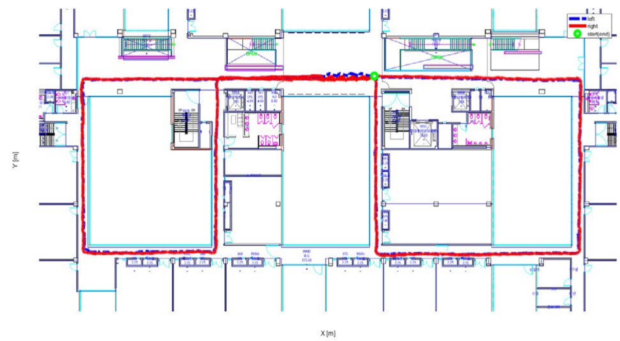

Fig. 9. Estimated position using proposed DF-PDR system.

sensors.

In the last experiment, three experimenters walked three times each along a 300 m long trajectory. The location estimation results for the experiment are shown in Table 4. As before, the return position error was confirmed by making the starting point, and the arrival point the same, and the value is 1.5 m. It can be seen that the proposed method estimates the position of pedestrians well. The position error is large compared to the first and second experiments because the length of the trajectory is long. Fig. 9 is the result of drawing the estimated trajectory for one of the experiments on the building drawing. Pedestrians walked the entire building along the corridor, and the estimated trajectory is well represented, and it can be said that it is well estimated as it does not penetrate rooms or walls.

5. CONCLUSION

This paper proposed a particle filter-based DR-PDR system that fuses position information using IMUs attached to both feet. The proposed method estimates the horizontal position with a particle filter considering the systematic drift found in the DF-PDR system. Moreover, the particle estimated in each PDR system is fused using a Gaussian mixture to create a location measurement. The proposed method can be implemented in real-time in an embedded system because the particle filter estimates only the horizontal position, and EKF estimates the velocity and attitude. Compared with the standalone PDR system, it was confirmed through an experiment that the location estimation accuracy is improved. Since the position error that gradually increases over time can be corrected, it is expected to provide a relatively stable position estimation performance to firefighters, even considering the mission time.

ACKNOWLEDGMENTS

This work was supported by Institute of Information & communications Technology Planning & Evaluation (IITP) grant funded by the Korea government (NFA) (No. 2019-0-01325, Developed of wireless communication tracking based location information system in disaster scene for fire-fighters and person who requested rescue).

AUTHOR CONTRIBUTIONS

Jae Hong Lee contributed to the conceptualization of the idea, analysis experiment results, and writing original draft. Seong Yun Cho contributed to support the analysis results and reviewed the manuscript. Chan Gook Park supervised the research and reviewed the manuscript as a project administrator. All authors discussed the proposed results.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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