Suppression of performance degradation in traveling direction estimation by using IMU and PCA for PDR

Masahiro Fujii<br>Department of Information Systems Science, Graduate School of Engineering, Utsunomiya University, 7-1-2 Yoto, Utsunomiya Tochigi 321-8585, Japan

Yuya Sakuma<br>Department of Information Systems Science, Graduate School of Engineering, Utsunomiya University, 7-1-2 Yoto, Utsunomiya Tochigi 321-8585, Japan

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#### Abstract

In this paper, we propose a new method to estimate a traveling direction for a pedestrian with a smart phone by using the Inertial Measurement Unit (IMU) and principal component analysis (PCA). Our estimator does not restrict a holding status of the smart phone. It is possible to estimate an attitude of the smart phone based on the IMU filter which makes use of values from sensors embedded in itself. We estimate a traveling direction of the pedestrian based on the PCA by using the output of the filter. However, this method essentially includes an indeterminacy problem which allows a direction reversal because the component of the PCA is non-directed graph. In this paper, we investigate a modified traveling direction estimation method in order to suppress a performance degradation caused by this problem. From experimental results, we show that the proposed estimator outperforms the conventional one.


Keywords: Pedestrian dead reckoning, Traveling direction estimation, Inertial measurement unit, Principal Component Analysis

## 1 Introduction

Several services by using location information such as navigation systems for the pedestrians are currently available with the growth of smart phones. A typical method to estimate the location of the mobile terminal is the Global Positioning Systems (GPS). It is possible to estimate the location by using received signals from more than four GPS satellites for three dimensional positioning. We need to measure the pseudo distance between the terminal and the satellite. This process assumes that a channel between the terminal and the satellite is the Line-Of-Sight (LOS). However, some shielding objects such as buildings in high-rise area may cut off the LOS. In this case, it is


Figure 1: Relative movement
difficult to estimate the location of the terminal because of a lack of the sufficient number of the observations from the GPS satellites[1]. On the other hand, we are concerned that an erroneous distance measurement, caused by the observation of reflected wave due to the buildings, results in serious error of the positioning. Moreover, we may be able to estimate the location of the terminal indoors because of the lack of the LOS from the satellites. It has been studied that the positioning system with another wireless systems such as the Wifi, the Bluetooth and so on instead of the GPS. However, there is no positioning system which is available everywhere because we cannot always use such wireless systems. Thus, we assume an intermittent positioning caused by the irregular disconnection of the GPS and the wireless systems even if we need a successive navigation system for the mobile terminal.

An alternative technique is useful to track the relative movement of the pedestrian with the mobile terminal and interpolate the estimates of the intermittent absolute positioning given by the previous positioning techniques such as the GPS. A technique to estimate the relative movement of object is referred to as Dead-Reckoning (DR) and the DR for the pedestrian is specially called Pedestrian DR (PDR). The PDR does not depend on circumference environment such as the shielding and reflecting objects (e.g. wall and ceiling) which deteriorates the positioning accuracy of the GPS. Because the PDR makes use of sensors mounted on the mobile terminal held by the pedestrian, it is possible to estimate the relative movement with a certain accuracy everywhere. The relative movement of the terminal held by the pedestrian consists of the direction and the distance between past and current positions as shown in Figure 1. It is possible to estimate the distance by calculating the product of the length of the stride and the number of the steps. In this paper, we focus on estimation methods of the traveling direction for pedestrian movement. In [2], a walking route has been estimated by using the integration of the accelerometer placed on toe. A PDR system by using gyroscope sensor and accelerometer has been developed in [3]. In this system, the acceleration and gyroscope sensors are, respectively, made available for a step counter and a traveling direction estimation. [4] has proposed a positioning system with the sensors and vision camera. In [5], a PDR system by using sensors in hand has been proposed. This system includes the estimation of the holding status of the terminal, the traveling direction, the step counter, and the length of the stride. The traveling direction estimator makes use of the geomagnetic sensor. Moreover, several systems have been devoted to the study of a fusion of the absolute positioning and the relative movement estimation. [6] has introduced to the radio frequency identifier tag and the map matching techniques into the fusion system. We have proposed a new fusion system by the Kalman filter[7].

The smart phones in the current marketplace are normally equipped with the sensors such as the accelerometer, the gyroscope, and the geomagnetic sensors which are useful for the relative movement estimation of the PDR. In several studies about the PDR, the sensors are places on a certain part of the human body such as waist, toe and so on. However, it is usually difficult to confine the holding status and the attitude of the sensors embedded in the smart phone for the


Figure 2: Examples of holding status of smart phone


Figure 3: Coordinate systems
pedestrian navigation system. In the usual cases, the pedestrian may walk with the smart phone in hand, and walk holding it and swing the arm in examples as shown in Figure 2. It may be stored in bag and pocket while the pedestrian walks. Although [5] has investigated the PDR system under the condition that the pedestrian holds the terminal with unconfined holding status, it relies on the geomagnetic sensor to estimate the traveling direction. However, the geomagnetic sensor may suffer from the surrounding magnetic materials such as reinforced constructions. Thus, we have proposed the new traveling direction estimation method for the PDR[8]. This method makes use of the Principal Component Analysis (PCA) based on the sensor values of the accelerometer and the gyroscope sensor. Though, this method essentially includes an indeterminacy problem which allows a direction reversal because the component of the PCA is non-directed graph. Our conventional estimator causes a coincidental reversal of direction due to this problem. Thus, we have proposed a new traveling direction estimation method in order to suppress a performance degradation caused by this problem[9]. Moreover, we have investigated the proposed method by introducing a new evaluation criterion and adding experimental evidence in [10]. In this paper, we report on a polished proposed method and a consolidation of our results. This paper is a revision of [9].

## 2 Coordinate systems

In this paper, we consider three coordinate systems in order to estimate the direction of movement of the pedestrian. A coordinate system which indicates the traveling direction of the movement does not identify that of the sensors of the smart phone. We call the coordinate system of the pedestrian P-coordinate system. In the P-coordinate system as shown in Figure 3(a), $P_{x}$ and $P_{y}$ are, respectively, defined as rightward and forward directions of the pedestrian. And $P_{z}$ is the direction of the cross product of $P_{x}$ and $P_{y}$ in the right-handed coordinate system, and is equal to vertical direction of the ground. Next, we introduce a world coordinate system as shown in Figure 3(b). In the W-coordinate system, $W_{x}$ and $W_{y}$ are, respectively, eastward and northward directions of the
earth. And $W_{z}$ is the direction of the cross product of $W_{x}$ and $W_{y}$ in the right-handed coordinate system, and is defined as vertical axis from the ground. The W-coordinate system corresponds to the geographical one. It is possible to define the W-coordinate system as alternative system as long as we can describe a structured geographical information such as room and passage. Note that the W-coordinate system does not always correspond to the P-coordinate system since we cannot relate the traveling direction of the pedestrian to the geographical information and it is possible to relate a rotation of the two coordinate systems which share the origin without translation. Thus, to estimate the direction of the movement is to estimate the relative rotation. "rotation" is used interchangeably with "coordinate transformation".

On the other hand, the sensors of the device are available for the estimation of the traveling direction of the pedestrian. We call the coordinate system of the device D-coordinate system. The sensor value is observed in the D-coordinate system as shown in Figure 3(c). In the D-coordinate system, $D_{x}, D_{y}$, and $D_{z}$ axes are, respectively, right, top, and vertical directions of the device screen. $D_{z}$ is the direction of the cross product of $D_{x}$ and $D_{y}$ in the right-handed coordinate system. This definition is available to most sensor platforms for the smart phone. Note that the D-coordinate system does not always correspond to the P - and W -coordinate systems because the attitude of the smart phone held by the pedestrian varies in accordance with the holding status and walking behavior as shown in Figure 2. The origin of the D-coordinate system is also in agreement with those of the P - and W -coordinate systems. The three coordinates systems are interrelated to the rotation each other.

## 3 Traveling direction estimation

Our goal is to estimate the relative rotation from the P-coordinate system to the W-coordinate system by using the observation of the sensor in the D-coordinate system. In this section, we discuss a new estimation method for the traveling direction based on the rotations among the three coordinate systems.

### 3.1 Rotation from D-coordinate system to $\mathbf{W}$-coordinate system

First, we explain how to estimate the relative rotation from the D-coordinate system to the Wcoordinate system. This corresponds to an estimation of the attitude of the device. A suitable combination of the tri-axis accelerometer and the tri-axis gyroscope sensor can provide an Inertial Measurement Unit (IMU) filter. Moreover, a Magnetic, Angular Rate, and Gravity (MARG) filter is available by adding the tri-axis magnetometer. It is possible to implement the IMU and MARG filters by simple calculation[11]. The IMU filter cannot estimate the rotation from the D-coordinate system to the W-coordinate system because it does not use the magnetometer which measures the earth's magnetic field. That is, although it can estimate the roll and pitch angles of the attitude of the device, it cannot do the yaw angle. On the other hand, the MARG filter can estimate these angles owing to the magnetometer. However, it may suffer from the magnetic distortion caused by ferromagnetic elements in the vicinity of the magnetometer. In this paper, we make use of the IMU filter for the estimation in order to avoid this concern. Then, it is necessary to conform the D-coordinate system to the W-coordinate system in the initial position.

### 3.2 Rotation from W-coordinate system to P-coordinate system

In this section, we discuss how to estimate the relative rotation from the W -coordinate system to the P-coordinate system based on the sensor value rotated from the D-coordinate system to the W-coordinate system by using the IMU filter. This corresponds to an estimation of the traveling direction of the pedestrian in the W -coordinate system. Although the rotation from the D-coordinate system to the W-coordinate system can be implemented by the mechanical method such as the IMU and MARG based on the properties of the acceleration of gravity and the earth's magnetic field, it is difficult to estimate a rotation from the W -coordinate system to the P -coordinate system in a similar fashion. It is necessary to consider behaviors of the sensors mounted on the smart phone


Figure 4: Acceleration value in $W_{x}-W_{y}$ plane and first principle component
based on walking activities of the pedestrian. Thus, we have proposed the estimation method for the traveling direction based on the PCA by focusing on a relationship the traveling direction and a forward and back movement with the walking activities[8]. We assume that a walking surface is a plane perpendicular to the direction of the acceleration of gravity i.e. $W_{z}$-axis is equal to $P_{z^{-}}$ axis. Then, the rotation from the W-coordinate system to the P-coordinate system corresponds to a rotation from $W_{x}-W_{y}$ plane to $P_{x}-P_{y}$ plane. Hereafter, we discuss a traveling direction estimation method in two dimensions.

Circles and solid lines in Figure 4 show an example of a projection of the acceleration values, rotated from D-coordinate system to W-coordinate system by the IMU filter for $T=1 \mathrm{~s}$, in $W_{x}-W_{y}$ plane. The pedestrian walks swinging one's arm with the smart phone clutched in one's hand in accordance with linear uniform motion as shown in the left of Figure 2. The traveling direction is equal to positive $W_{y}$-axis, i.e. upper direction on paper. The number of the samples of the acceleration indicated by the circles is equal to 50 because the sampling rate of the accelerometer and observation period $T$ are, respectively, equal to 50 Hz and 1 s . And, a projection of the first principle component on $W_{x}-W_{y}$ plane is shown by a dotted line based on these observations of the acceleration. As shown in Figure 4, the traveling direction strongly correlates with the first principle component of the PCA. However, since the principle component is non-directed graph, the direction estimation essentially includes the indeterminacy problem which allows a direction reversal. For example, it is impossible to decide between north and south, in other words, positive and negative directions in $W_{y}$-axis in Figure 4. We must choose between a direction estimate based on the first principle component and its rotation through $180^{\circ}$.

### 3.2.1 Conventional estimator and its problem

Our conventional estimation method in [8] assumes that a change in direction of the pedestrian is less than $90^{\circ}$ in the sampling intervals. This is a reasonable assumption by considering the walking behavior of the pedestrian because the sampling interval of the sensors embedded in the smart phone is usually shorter than a speed of the change in direction. The conventional method simply selects an estimate more closely to that of the direction at the previous sampling time from two directions given by the first principle component, which is the non-directed graph, as an estimate at the current sampling time. Let us define $\theta_{l}$ as true direction of the pedestrian at discrete time $l$. And $\tilde{\theta}_{l, 1}^{(T)}$ and


Figure 5: An example of direction reversal
$\tilde{\theta}_{l, 2}^{(T)}$ represent two directions provided by the projection of the first principle component based on the acceleration values rotated from D -coordinate system to W -coordinate system by the IMU filter for $T$ in $W_{x}-W_{y}$ plane at discrete time $l$. Moreover $u\left(\theta_{l, 1}\right)=-u\left(\theta_{l, 2}\right)$ holds where $u(\theta)=\cos \theta+j \sin \theta$. $u(\theta)$ is a complex number with argument $\theta$ and its absolute value is equal to 1 . The argument is define by $\theta=\arg (u(\theta)) . \tilde{\theta}_{l, 1}^{(T)}$ and $\tilde{\theta}_{l, 2}^{(T)}$ mean candidates of the estimate of $\theta_{l}$ and depend on interval of the IMU filter $T$. Although an estimate of direction is equal to one direction among the first principle component of the PCA, these candidates are represented by $\sim$ and subscript number 1 and 2. Then, an estimate by the conventional method is given by

$$
\begin{equation*}
\hat{\theta}_{l}^{(T)}=\arg \min _{\theta \in\left\{\hat{\theta}_{l, 1}^{(T)}, \tilde{\theta}_{l, 2}^{(T)}\right\}}\left\|u\left(\hat{\theta}_{l-1}^{(T)}\right)-u(\theta)\right\| \tag{1}
\end{equation*}
$$

where $\|\cdot\|$ means the Euclidean norm. The estimate is represented by $\hat{\imath}$ and is selected from two candidates $\tilde{\theta}_{l, 1}^{(T)}$ and $\tilde{\theta}_{l, 2}^{(T)}$. Note that the estimate depends on interval $T$ for the IMU.

However, the conventional estimator may cause the reversal through $180^{\circ}$ of the traveling direction under a specific condition. Figure 5 shows an example of this phenomenon. We assume estimate $\hat{\theta}_{l-1}^{(T)}$ as shown in $5(\mathrm{a})$. In this example, we assume that true directions $\theta_{l}, \theta_{l+1}$, and $\theta_{l+2}$ are equal to $90^{\circ}$, respectively. This assumption of the true constant directions is for a simple explanation and they are not always equal to $90^{\circ}$. At time $l$ in Figure $5(\mathrm{a})$, although we can obtain two estimates $\tilde{\theta}_{l, 1}^{(T)}$ and $\tilde{\theta}_{l, 2}^{(T)}$ from the first principle component, the conventional estimator selects $\tilde{\theta}_{l, 1}^{(T)}$ as estimate $\hat{\theta}_{l}^{(T)}$ based on Equation (1) because the angle difference is smaller. Next, at time $l+1$ as shown in Figure $5(\mathrm{~b})$, it selects $\tilde{\theta}_{l+1,1}^{(T)}$ as $\hat{\theta}_{l+1}^{(T)}$ in a similar fashion. From Figure $5(\mathrm{~b})$, it is clear that $\tilde{\theta}_{l+1,1}^{(T)}$ is a suitable estimate because $\theta_{l+1}=90^{\circ}$.

On the other hand, when $\tilde{\theta}_{l+1,1}^{(T)}$ and $\tilde{\theta}_{l+1,2}^{(T)}$ are given as shown in Figure $5(\mathrm{c})$, the conventional estimator unfortunately selects $\tilde{\theta}_{l+1,2}^{(T)}$ as $\hat{\theta}_{l+1}^{(T)}$ due to equation (1). It is clear that $\tilde{\theta}_{l+1,1}^{(T)}$ is preferable


Figure 6: Flow of the proposed estimator
to $\tilde{\theta}_{l+1,2}^{(T)}$ as the estimate because $\theta_{l+1}=90^{\circ}$. And what is worse, at time $l+2$ as shown in Figure $5(\mathrm{~d})$, it selects $\tilde{\theta}_{l+2,2}^{(T)}$ as $\hat{\theta}_{l+2}^{(T)}$ although it is clear that $\tilde{\theta}_{l+2,1}^{(T)}$ is better than $\tilde{\theta}_{l+2,2}^{(T)}$. As was the case in this example, even if the absolute value of an error of direction estimation is less than $90^{\circ}$, the reversal of direction estimation occurs when the cumulative value of successive erroneous estimates for several samples exceeds $90^{\circ}$. The erroneous reversal is continued until the same phenomenon reoccurs incidentally. Although this failure occurs with low frequency, it results in serious problems to the PDR.

### 3.2.2 Proposed estimator

In this section, we propose a traveling direction estimation method in order to improve the previous problem of the conventional one. Figure 6 shows a flow of the proposed estimator. A method of obtaining $\tilde{\theta}_{l, 1}^{(T)}$ and $\tilde{\theta}_{l, 2}^{(T)}$ from the sensor values, i.e., the acceleration and the angular velocity measured on the accelerometer and the gyroscope sensor, by using the IMU filter and the PCA of the proposed estimator is the same with that of the conventional one. Although the conventional method selects the direction closest to the previous estimate, the proposed one selects the direction closest to the average value of the estimates for $K$ samples. In the proposed method, the estimate of direction at time $l$ is given by

$$
\begin{equation*}
\hat{\theta}_{l}^{(T, K)}=\arg \min _{\theta \in\left\{\min _{l, 1}^{(T)}, \tilde{\theta}_{l, 2}^{(T)}\right\}}\left\|u\left(\bar{\theta}_{l-1}^{(T, K)}\right)-u(\theta)\right\| \tag{2}
\end{equation*}
$$

where

$$
\begin{equation*}
\bar{\theta}_{l-1}^{(T, K)}=\arg \left(\sum_{i=l-K}^{l-1} u\left(\hat{\theta}_{i}^{(T, K)}\right)\right) \tag{3}
\end{equation*}
$$

where function $\arg ()$ returns an argument of the complex number. It is possible to avoid the reversal of direction caused by the cumulative value of successive erroneous estimates owing to a smoothing effect. The proposed estimator depends on not only interval $T$ for the PCA but also the number of integration $K$ for the smoothing. When $K=1$, the proposed estimator in Equation (2) completely corresponds to the conventional one in Equation (1) since $\bar{\theta}_{l}^{(T, 1)}=\hat{\theta}_{l}^{(T, 1)}=\hat{\theta}_{l}^{(T)}$.

Table 1: Trial numbers associated by holding status and individual pedestrian

| Pedestrian Status | In hand | Swing arm | In bag |
| :---: | :---: | :---: | :---: |
| A | $1-3$ | 9,10 | 20,21 |
| B | 4,5 | 11,12 | $22-26$ |
| C | $6-8$ | $13-19$ | $27-31$ |
| D | 32 | 41 | 50 |
| E | 33 | 42 | 51 |
| F | 34 | 43 | 52 |
| G | 35 | 44 | 53 |
| H | 36 | 45 | 54 |
| I | 37,38 | 46,47 | 55,56 |
| J | 39,40 | 48,49 | 57,58 |

## 4 Experimental results

In this section, we compare estimation performances of the proposed method described in Section 3.2 .2 with those of the conventional one in Section 3.2.1. It is possible to apply the traveling direction estimators investigated in this paper to normal use of the smart phone independent of its attitude in principle. As an example, we assume the following three holding statuses of the smart phone as shown in Figure 2.

In hand the pedestrian walks holding the smart phone clutched in one's hand on one's chest.
Swing arm the pedestrian walks swinging one's arm with the smart phone clutched in one's hand.
In bag the pedestrian walks with the bag containing the smart phone saddled on one's back.
Experimental participants are three men in their early twenties and the number of trials is equal to $N=31$. Table 1 shows a correspondence table of trial number from 1 to $N=31$ associated by the three holding statuses and the three experimental participants. A smart phone for our experiment is Nexus 5 provided by Google and the sampling rates of the accelerometer and gyroscope sensor are equal to 50 and 100 Hz , respectively. The pedestrian goes from a start point in Figure 7(a) in the negative direction of $W_{x}$-axis at the constant speed. After that, he turns $90^{\circ}$ to the right and goes in the positive direction of $W_{y}$-axis at the same speed. In our experiment, a motion image of the pedestrian is photographed by a video camera as shown in Figure 7 (b). We identify true directions at certain times by comparing the time-stamp of the video with that of the smart phone.

Figure 8 shows estimates of the traveling direction of the conventional and proposed estimators as a function of elapsed time in the case of the 31-st trial. As shown in Figure 7(a), the true direction of the pedestrian is equal to the negative $W_{x}$-axis, i.e. $\theta_{l}=180^{\circ}$ from the start to 48.5 s which is the time matched by the video. Since he turns $90^{\circ}$ to the right at 48.5 s , the true direction is equal to $\theta_{l}=90^{\circ}$, which corresponds to the positive direction of $W_{y}$-axis, from 48.5 s to the end as shown by dotted line of Figure 8.

First, we discuss an effect of interval $T$ of the PCA on convergence performances of the estimator. The estimators investigated in this paper apply the PAC to the acceleration values in W-coordinate system for $T[\mathrm{~s}]$ as shown in Figure 6 . When $T=1 \mathrm{~s}$, the PCA makes use of 50 samples of the acceleration values as shown in Figure 4 because the sampling rate of the accelerometer is equal to 50 Hz . As $T$ grows larger, it is possible to suppress variations of the estimate because of a smoothing effect with the increasing number of the samples of the acceleration values. However, the PCA with large $T$ has a poor response to the change in direction because the principle component involves many past samples. By comparing performances of $T=1.0$ and 4.8 s of the conventional method depicted by dashed-dotted and dotted lines in Figure 8 (left part of curve of $T=4.8 \mathrm{~s}$ is filled by solid line), the estimator when $T=1.0 \mathrm{~s}$ provides more rapid response although its estimates vary.


Figure 7: Experimental route and scene

It is necessary adaptively to decide interval $T$ by considering the response to the change in direction, the variation of the estimate, and power consumption for the sensors.

The reversal of the estimate in the conventional estimator described in Section 3.2.1 occurs only when the cumulative value of successive erroneous estimates for several samples exceeds $90^{\circ}$. An involuntary reversal of direction in the conventional estimator when $T=4.8 \mathrm{~s}$ in Figure 8 are observed at around 58 s . Then, in the conventional estimator depicted by the dotted line, the estimate of direction is rapidly shifted and the reversal is continued until the end. In contrast, the proposed estimator with $T=4.8 \mathrm{~s}$ and $K=10$ can recover a suitable estimate of direction although it causes an instantaneous large error owing to the cumulative erroneous estimates. The performance of the proposed estimator almost corresponds to that of the conventional one before about 58 s . Thus, the proposed estimator can suppress the reversal of direction of the estimate without performance degradation.

Next, we evaluate average performances of the proposed estimator. We redefine $\theta_{l}[n]$ for true direction at time $l$ in the $n$-th trial and express its estimate as $\hat{\theta}_{l}^{(T, K)}[n]$ which depends on parameters $(T, K)$ in the proposed estimator. In the conventional estimator, $K=1$. Then, let us define Root Mean Squared Error (RMSE) for the $n$-th trial as

$$
\begin{equation*}
\operatorname{RMSE}^{(T, K)}[n]=\sqrt{\frac{1}{4 L_{n}} \sum_{l=0}^{L_{n}-1}\left\|u\left(\hat{\theta}_{l}^{(T, K)}[n]\right)-u\left(\theta_{l}[n]\right)\right\|^{2}} \tag{4}
\end{equation*}
$$

where $L_{n}$ denotes the number of samples in the $n$-th trial and depends on trial index $n$ even if the same pedestrian walks along the same route. Since the absolute value of $u(\cdot)$ is equal to 1 , $0 \leq \operatorname{RMSE}^{(T, K)}[n] \leq 1$ is held. If $u\left(\hat{\theta}_{l}^{(T, K)}[n]\right)=-u\left(\theta_{l}[n]\right)$ for $l=0, \cdots, L_{n}-1$, i.e. the estimate is always the rotation through $180^{\circ}$ of true direction, $\operatorname{RMSE}^{(T, K)}[n]=1$ at the worst. Figure 9 shows RMSE performances for the $n=27$-th trial as a function of interval $T$ for the PCA by comparing the proposed estimator plotted as circles with the conventional one plotted as triangles. When $T<1$ s , both estimators result in unstable RMSE because the number of samples for the PCA as shown in Figure 4 is not enough to estimate the direction with high accuracy. It is possible to improve RMSE as $T$ grows larger and achieve the lowest RMSE at $T=1 \mathrm{~s}$. The RMSE grows with an another increase in $T$ because the principle component of the PCA involves many past samples. When $1 \leq T \leq 5 \mathrm{~s}$, the proposed estimator can provide stable RMSE performances although the


Figure 8: Estimate of traveling direction v.s. elapsed time
conventional one occasionally causes the direction reversal as shown in Figure 8. However, both estimators deteriorate the RMSE performances because of the reversal of the estimate when $T>5$ s.

Figure 10 shows RMSE performances as a function of trial number $n$ related to the three experimental participants and the three holding statuses of the smart-phone listed in Table 1. Upper, lower lines of error bar and plot mean the maximum, minimum and average values of the RMSE for $1 \leq T \leq 5 \mathrm{~s}$, respectively. In the cases of "In hand" and "Swing arm" for $n=1, \cdots, 19$, the proposed estimator always outperforms the conventional one because it is possible to suppress the reversal of direction. However, the conventional estimator occasionally beats the proposed one in the case of "In bag" for $n=20, \cdots, 31$. Because the attitude of the smart phone in this holding status varies rapidly, an erroneous attitude estimation may deteriorate the RMSE performance.

Next, we show some experimental results in the case that the pedestrian makes U-turn as shown in Figure 11. In this experiments, the pedestrian goes in the positive direction of $W_{y}$-axis at the constant speed. At a cone located just 10 meters from the start point, the pedestrian quickly makes U-turn and steps foot back into the start point.

We have 27 trials for this U-turn experiments indexed by $n=32, \cdots, 58$ which follows Figure 10. The added number of the pedestrians are equal to $7(\mathrm{D}, \ldots, \mathrm{J})$ as shown in Table 1. Figure 12 shows RMSE performances in the case that $T=2.9 \mathrm{~s}$. In this example, the proposed estimator provides the same RMSE with the conventional one because the conventional estimator does not cause the reversal of direction when the pedestrian walks in a straight line. Thus, both the estimators make no difference for the RMSE. In the case of "In hand", both the estimators can work well. However, because of the unstable stand of the terminal, it is impossible to estimate the direction respectably.

## 5 Conclusions

In this paper, we proposed the new method to estimate the traveling direction by using the IMU and the PCA for the PDR. The conventional estimator essentially includes the indeterminacy problem which allows a direction reversal since the principle component is non-directed graph. Although the conventional method selects the direction closest to the previous estimate, the proposed one selects the direction closest to the average value of the estimates for $K$ samples. The proposed


Figure 9: RMSE v.s. PCA interval $T$ in the $n=27$-th trial
estimator can improve the reversal owing to the averaging effect. The pedestrians walked with the smart phone along the experimental route and we evaluated the traveling direction estimators based on the observations from the sensors. From the experimental results, the proposed estimator can suppress the unexpected reversal of the traveling direction caused by the conventional one.

As a future work, we are developing a modified direction estimator independent of the initial setting. We are improving the proposed direction estimator for quick motion change of the pedestrian.

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## conventional estimator ${\max \left\{\mathrm{RMSE}^{(T, K=1)}[n]\right\}}^{\operatorname{avg}\left\{\mathrm{RMSE}^{(T, K=1)}[n]\right\}}$ $\min \left\{\mathrm{RMSE}^{(T, K=1)}[n]\right\}$ proposed estimator $\max \left\{\operatorname{RMSE}^{(T, K=10)}[n]\right\}$ avg\{RMSE $\left.{ }^{(T, K=10)}[n]\right\}$ $\min \left\{\operatorname{RMSE}^{(T, K=10)}[n]\right\}$

Figure 10: RMSE v.s. trial number (L-shaped)


Figure 11: U-turn walking route
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Figure 12: RMSE v.s. trial number (U-turn)
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