An Adaptive Heading Estimation Method based on Holding Styles Recognition Using Smartphone Sensors

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***Abstract*—Pedestrian Dead Reckoning (PDR), which comes with many sensors integrated into widely available smartphones, is known as one of the most popular indoor positioning techniques. Sensors such as accelerometers, gyroscopes, and magnetometers are used to determine three important components in PDR: step detection, step length estimation, and heading estimation. Among them, the last component is the most challenging since a small heading error accumulates to produce a very large positioning error, especially when the pedestrian holds the smartphone in unconstrained styles such as swinging the phone freely along the pedestrian's walking direction or putting the phone into the pants' front pockets. The research proposes an adaptive heading estimation method to deal with heading errors caused by smartphone holding styles. The novelties are described as follows. Firstly, the proposed method attempts to classify the four basic smartphone holding styles using a machine learning algorithm based on simple features of acceleration values to give pedestrians more freedom during the walking period. Secondly, the proposed method adaptively combines the two heading estimation methods, which are calculated from the integrated sensors, to determine the walking direction for different smartphone holding styles. The experimental results show that the proposed heading estimation method achieves average heading errors of less than 30 degrees when testing in two different walking paths with the smartphone held in dynamic styles. It helps to reduce the heading errors by more than 15% compared to previous heading estimation methods.**

***Index Terms*—Adaptive Heading Estimation Method, Holding Styles Recognition, Smartphone Sensors**

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I. Introduction

OVER the last 20 years, Location-Based Services (LBS) have received a lot of attention due to their practical applications such as navigation, emergency rescue, monitoring/surveillance, and other areas. Currently, the Global Navigation Satellite System (GNSS) is providing good positioning results outdoors. However, its performance degrades in signal-blocked environments, such as indoors, due to multipath effects and signal attenuation [1]. Furthermore, in urban areas, people often spend more than 80% of their time staying or working indoors [2–4]. Therefore, Indoor Positioning Systems (IPS) have been focused on and developed to cover the needs of positioning in indoor environments.

Up to now, there are many technologies used to track the position of a pedestrian. They can be divided into two groups: infrastructure-dependent and infrastructure-independent. The former group needs information from the building's infrastructure and can be represented by some popular technologies such as Bluetooth [5, 6], Wi-Fi [7–9], visible light communication [10, 11], and others. However, the performance of these depends on dedicated infrastructure, which

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is not suitable when deploying to big areas, such as shopping malls or airports. On the other hand, the latter group does not require information from the building's infrastructure to determine the pedestrian's position. Some famous technologies in this group are vision-based [12, 13] and inertial-based [14–17]. The Pedestrian Dead Reckoning (PDR), as one technique for the inertial-based system, has become a promising solution for indoor positioning by utilizing many sensors on smartphones, indispensable devices in modern lives. The pedestrian's relative position can be calculated by knowing the initial setup position and some updated information during the walking period. However, this technique suffers from the drift of the sensors, which causes cumulative positioning errors after a long working period. Therefore, it is essential to mitigate the limitation of the built-in sensors to improve the performance of PDR.

The PDR technique involves three dominant components: step detection, step length estimation, and heading estimation. Using the accelerometer and gyroscope, the researchers propose different methods to solve the step detection problem, such as peak detection [18], zero-crossing [19], deep learning [20], and others. These sensors are also used to estimate the step length. Principal Component Analysis (PCA) [21], analyzing the frequency of walking behavior [18], and deep learning [22, 23] are some methods that have been applied to increase the accuracy of step length estimation.

Heading estimation, as one of the three crucial components of the PDR systems, can be determined by utilizing different sensors in the smartphone. The absolute walking direction of a pedestrian is estimated using a magnetometer. However, interference from the surrounding environments degrades the heading accuracy. Meanwhile, the gyroscope can provide the relative heading results by integrating iteratively the angular rate values. The drawback of using a gyroscope comes from the measurement bias and noise. Thus, there should be combinations of many sensors to estimate the pedestrian's heading efficiently [24, 25]. The complementary filter [26–28] and Kalman filter [29–31] are some solutions to fuse the values from different sensors.

Commonly, the heading is determined with the initial assumption that the pedestrian always holds the smartphone in front of the pedestrian's body [32, 33], which means that the heading misalignment between the pedestrian and the smartphone remains constant, and by eliminating the heading offset, the pedestrian's heading can be estimated. Nevertheless, in real situations, the pedestrian can hold the smartphone in different styles which leads to changes in the heading misalignment angles. Many methods have been proposed to remove restrictions on the user's phone possession.

In previous research [34], the Finite State Machine (FSM) is used to detect the three smartphone holding styles. Then, an adaptive offset compensation scheme is developed to improve the heading accuracy. This method, however, requires the pedestrian to walk several steps to acquire a stable heading estimation. The PCA method is utilized to handle the holding styles in which the smartphone's heading dynamically changes, such as when swinging the phone or putting the phone into the pocket. Meanwhile, previous research has applied the PCA method to the acceleration values in the horizontal plane [35]. Next, a PCA-based method is proposed while processing the accelerations in the global coordinate system to improve the performance of the previous research [36]. However, the 180-degree ambiguity is the main problem of using this method since it originally cannot determine whether the pedestrian's walking direction is pointing forward or backward compared to the right direction.

Heading estimation plays a very important role in the PDR system since a small heading error may cause a big positioning error. Moreover, the unconstrained smartphone holding styles make the heading estimation a big challenge. In the research, an adaptive heading estimation method based on different holding styles is proposed to deal with the issues of the heading estimation when pedestrians change their holding styles, especially the unconstrained styles such as swinging the phone freely along the pedestrian's walking direction or putting the phone into the pants' front pockets while walking. The main contributions are as follows:

- A machine learning method is applied to classify the four common smartphone holding styles using simple features.
- An adaptive heading estimation method that combines the two methods to improve heading accuracy is presented. The proposed method is adapted for each classified holding style.
- Experimental results show better accuracy and robustness of the proposed method compared to other heading estimation methods.

II. Research Method

A. Overview

Figure 1 presents an overview of the proposed method, which includes two main components: holding style recognition and heading estimation. The input values come from the accelerometer, the gyroscope, and the magnetometer. The sensors' values are put through a low-pass filter before being applied to the

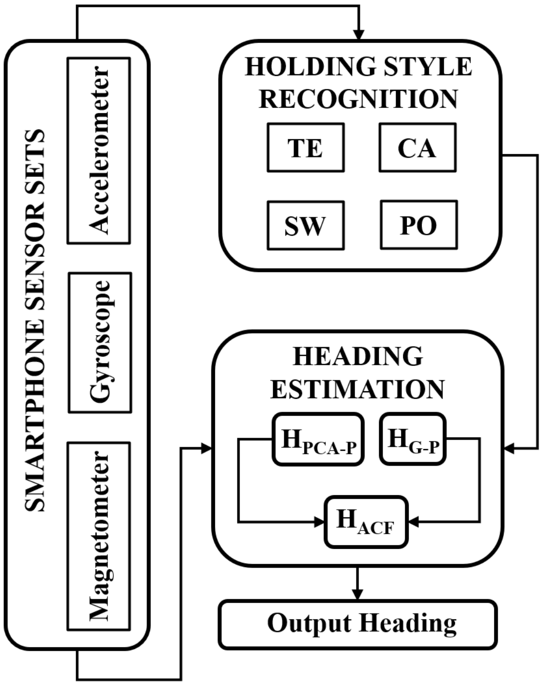

Fig. 1. Overview of the proposed method. It consists of holding the smartphone in front of the pedestrian's body for reading or texting (TE), holding the smartphone against the ears for making a phone call (CA), swinging the phone freely along the pedestrian's walking direction (SW), and putting the phone into the pants' front pockets (PO), PCA-based heading H_{PCA-P}, gyroscope-based heading H_{G-P}, and the proposed adaptive heading H_{ACF}.

two components. In the beginning, different smartphone holding styles are classified using the machine learning method Extra Tree (ET).

In the research, the holding styles include four styles, namely, holding the smartphone in front of the pedestrian's body for reading or texting (TE), holding the smartphone against the ears for making a phone call (CA), swinging the phone freely along the pedestrian's walking direction (SW), and putting the phone into the pants' front pockets (PO), respectively. Among the four holding styles, the TE and CA can be considered static styles since the smartphone's heading will not change much during the walking period. Meanwhile, the SW and PO can be considered dynamic styles since the smartphone's heading changes dynamically depending on the movement of the arm or leg of the pedestrian.

The heading estimation component includes three heading outputs: The PCA-based heading H_{PCA-P}, gyroscope-based heading H_{G-P}, and proposed adaptive heading H_{ACF}. The H_{PCA-P} is calculated from the accelerometer and magnetometer, while the H_{G-P} is calculated from the two aforementioned sensors and the gyroscope.

Then, the two headings are combined using an adaptive complementary filter to compute the third heading H_{ACF}. It should be noted that the heading values from the three methods are calculated in the global coordinate system by applying the rotation matrix. Based on the classified smartphone holding styles, the suitable heading method among the three implemented ones is chosen as the final heading output of the pedestrian.

B. Holding Style Recognition Method

The raw data for the holding style recognition is recorded from the triaxial accelerometers of the two smartphones, i.e., Samsung Galaxy S8 and Nexus 5. Three subjects (all males) have participated in the data collection. The sampling rate is 30 Hz. The acceleration values along the three axes are put through the 5^{th}-order Butterworth low-pass filter with a cut-off frequency of 5 Hz to remove the high-frequency components, i.e., the noise.

In the beginning, 22 statistical features in the time domain are chosen based on some previous works [37–39]. These features are extracted from the filtered accelerations at every sliding window of 60 samples, corresponding to 2 s, with 80% overlap. A simple method is proposed, including two steps to reduce the number of selected features: combination and permutation. At first, the combination is applied to choose the best result while using minimal features. However, ET,

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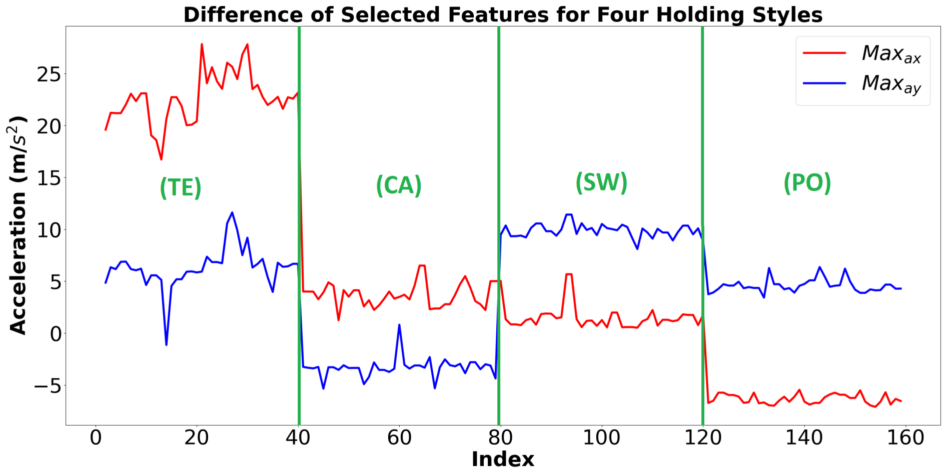

Fig. 2. Difference of selected features for four holding styles.

which is the chosen classifier, selects the split points randomly. Thus, the permutation is applied to choose the best combination of features by order arrangement.

After using the two above steps, only two features, which are the maximum values of the x-axis and the y-axis of the accelerometer, i.e., Max_{ax} and Max_{ay} in a sliding window, are selected to classify the four holding styles. Figure 2 shows the difference between the two chosen features for four styles.

In the research, the ET algorithm is applied for holding style recognition. This algorithm’s idea is basically similar to the popular Random Forest (RF) algorithm [40]. Both algorithms use a random subset of features and multiple decision trees to determine the output. ET uses the entire learning samples to grow the trees. Furthermore, ET selects a random split to divide the parent node into two random child nodes. Therefore, it has a lower variance as well as a faster running time than RF.

C. Principal Component Analysis (PCA)-Based Heading Estimation Method

A method is proposed to estimate the heading using acceleration values with the help of the PCA method when the device is in a pocket [35]. In this method, the maximum variance of the horizontal accelerations is parallel with the forward walking heading. In contrast, the minimum variance of the horizontal accelerations is parallel with the lateral direction. The heading values are calculated from the corresponding eigenvalues of the sorted first and second eigenvectors from highest to lowest since they represent the forward and lateral walking directions. Figure 3 shows the eigenvector extraction from the PCA method to estimate the walking direction.

The problem with PCA-based heading is finding the right forward heading since it cannot know whether the pedestrian is moving forward or backward, which is called the 180-degree ambiguity problem. To solve this, the PCA-based heading is simply compared to the gyroscope-based heading, which is described in the following sections. If the difference between the two headings is smaller than 180 degrees, the current PCA-based heading will be kept. If it is not, the heading will add 180 degrees.

Two factors that can affect the result are considered to improve the performance of the basic PCA method for heading estimation: the moment when the method should be executed during the walking period and the number of acceleration values that should be put into the PCA method. The first factor aims to improve the heading values of the unconstrained holding styles by finding the moment when the heading of the smartphone is the same as the pedestrian’s walking direction. Meanwhile, the second factor is considered since the small number of acceleration values will affect the variation of the values in the horizontal plane. It eventually affects the heading estimation results.

As the first factor, for the cases of the SW or PO, when the arm (in case of SW) or the leg (in case of PO) is perpendicular to the ground, the heading value extracted around this moment is supposed to be parallel to the real walking direction of the pedestrian. Figure 4 shows one gait cycle divided into seven sub-phases of the two main phases: stance (1–4) and swing (5–7).

From Fig. 4, the PCA method is deployed at the moments of the sub-phases (3) and (6), which are the mid-stance and mid-swing. It is assumed that angular velocity becomes maximum at these moments. The system tries to find the peak of the magnitude of

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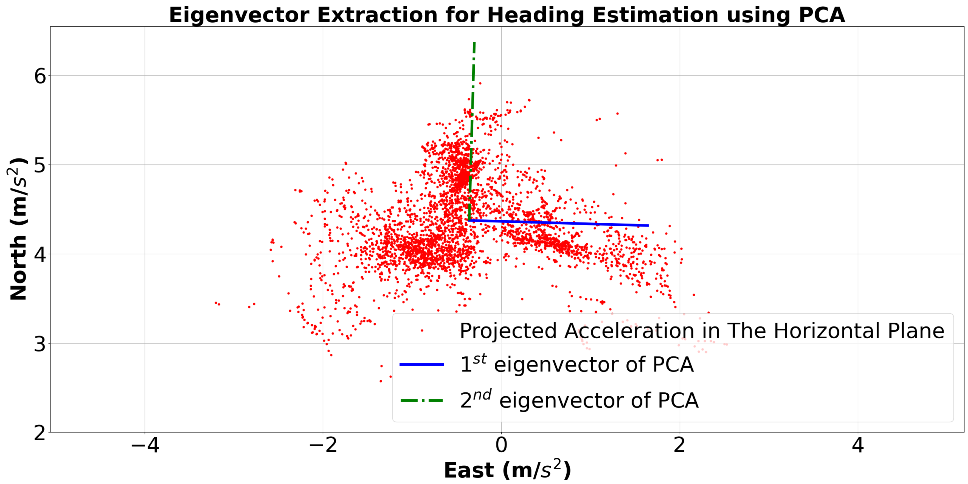

Fig. 3. Eigenvector extraction for heading estimation using Principal Component Analysis (PCA).

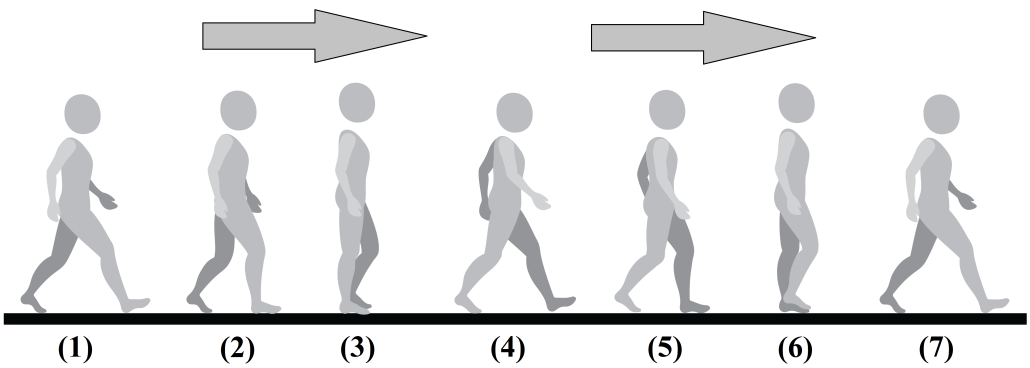

Fig. 4. Pedestrian's gait cycle.

TABLE I
COMPARISON OF TWO PRINCIPAL COMPONENT ANALYSIS (PCA) METHODS.

	Error (Degree)	
	HPCA-O	HPCA-P
Max.	85.69	37.31
Min.	0.01	0.01
Average	12.35	11.41
Std. Dev.	11.17	9.32

Note: Original Principal Component Analysis (PCA)-based heading ($H_{PCA\text{-}O}$) and Principal Component Analysis (PCA) -based heading executed at peak moment ($H_{PCA\text{-}P}$).

gyroscope values, i.e., $\|\vec{\omega}\| = \sqrt{{\omega_x}^2 + {\omega_y}^2 + {\omega_z}^2}$ in a given window, i.e., buffer. Then, the PCA method is applied with the acceleration values around the peak.

Figure 5 shows the difference between heading values estimated by the original PCA method ($H_{PCA\text{-}O}$), which is executed whenever a sufficient number of acceleration values is put into the buffer, and the PCA method is executed at the peak moment ($H_{PCA\text{-}P}$). Table I presents the comparison of the two methods in the SW case when the pedestrian walks in a straight line. From Table I, the maximum and average heading errors of the $H_{PCA\text{-}P}$ are both smaller than the $H_{PCA\text{-}O}$.

The second factor that can affect the performance of the PCA-based heading method is the number of acceleration values put into the buffer for execution. Figure 6 shows the heading errors of a different number of accelerations.

In the empirical experiment, with the number of values running from 10 to 100, the results show that a buffer of 60 samples is good enough for the PCA method. It should be noted that the main sampling rate is 30 Hz, which means that 60 samples are collected in two seconds. In the research, the PCA heading is calculated by considering those two factors together.

D. Gyroscope-based Heading Estimation Method

The magnetometer can provide the absolute heading. Meanwhile, the gyroscope can provide the relative

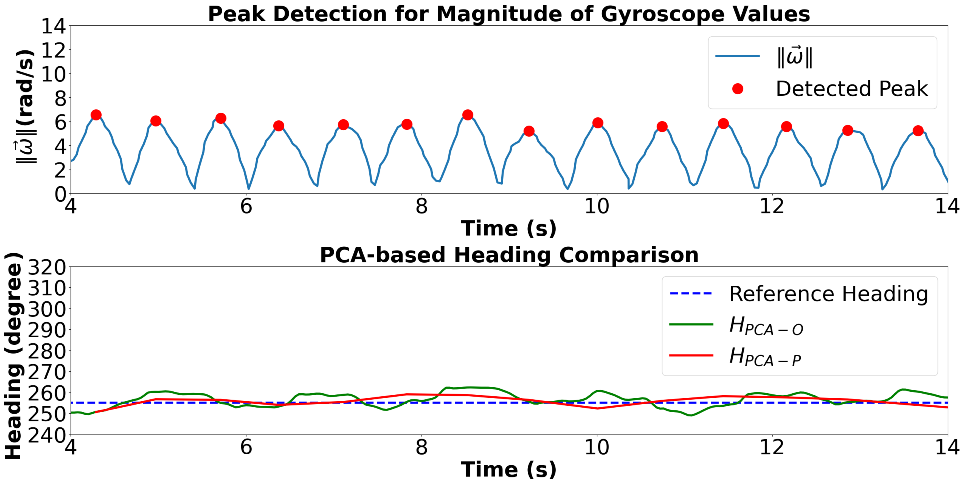

Fig. 5. The difference in heading estimation between two Principal Component Analysis (PCA)-based methods.

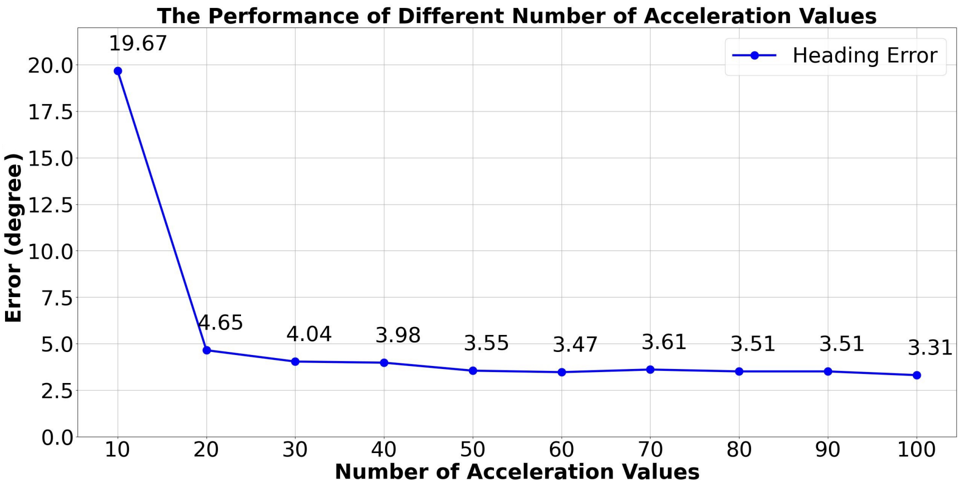

Fig. 6. The heading errors when using a different number of acceleration values for the Principal Component Analysis (PCA) method.

heading with the initial setup heading. The magnetometer itself is good for estimating the heading in mid-to-long time intervals. However, it is strongly affected by the surrounding interference, especially in indoor environments with lots of electronic devices. Meanwhile, the gyroscope can give a good heading result in short time intervals, but it drifts over time. Therefore, a method is proposed to fuse the three sensors to remove the disadvantages as well as to utilize the advantages of the sensors [24]. The diagram of the method is shown in Fig. 7.

From Fig. 7, the absolute heading $\mathrm{H}_{\mathrm{m/a}}$ is calculated from the accelerometer and the magnetometer in the global coordinate system. However, as aforementioned, this heading is affected by magnetic interference. So, the result should be put through a low-pass filter to remove the noise. The gyroscope, at the same time, is integrated to estimate the relative heading H_{g} by multiplying the values with the exact time interval, i.e., the time difference between two samples. The drift of the gyroscope after time can be solved by applying the high pass filter since the missing data can be replaced by the values from $\mathrm{H}_{\mathrm{m/a}}$. Hence, the complementary filter, as proposed in [41], is applied to fuse the two headings to extract the optimal heading $\mathrm{H}_{\mathrm{G\text{-}O}}$ as in Eq. (1). It has α of 0.97, which means $\mathrm{H}_{\mathrm{G\text{-}O}}$ is mainly dependent on the gyroscope.

$$H_G = \alpha H_g + (1 - \alpha) H_{m/a}. \tag{1}$$

It is worth noting that the initial heading for the H_{g} comes from the absolute heading $\mathrm{H}_{\mathrm{m/a}}$ since the H_{g} is just a relative heading. After that, the heading changes are calculated from the angular changes of the gyroscope. The gyroscope-based heading $\mathrm{H}_{\mathrm{G\text{-}P}}$ is

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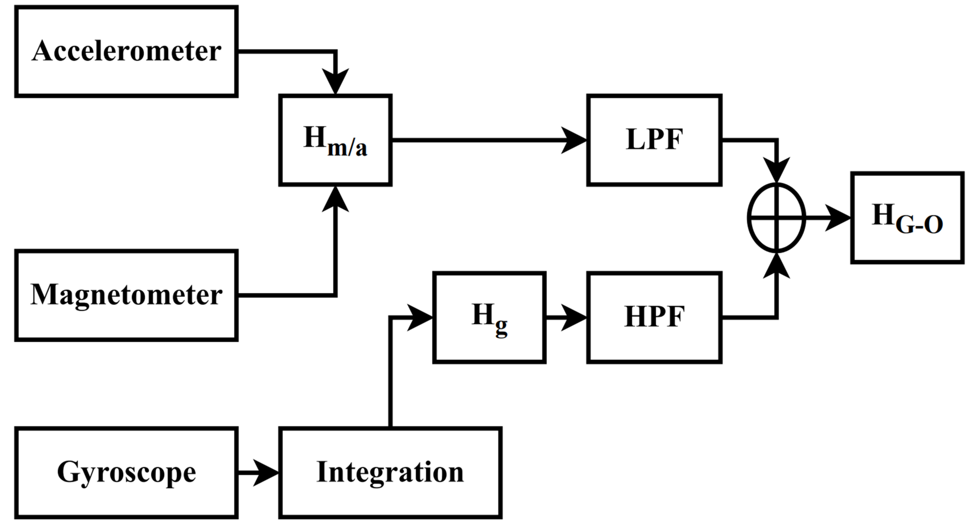

Fig. 7. The diagram of the gyroscope-based heading estimation method. Absolute heading calculated from the accelerometer and the magnetometer ($H_{m/a}$), relative heading calculated from the gyroscope (H_g), heading calculated from $H_{m/a}$ and H_g using the complementary filter ($H_{G\text{-}O}$), Low-Pass Filter (LPF), and High-Pass Filter (HPF).

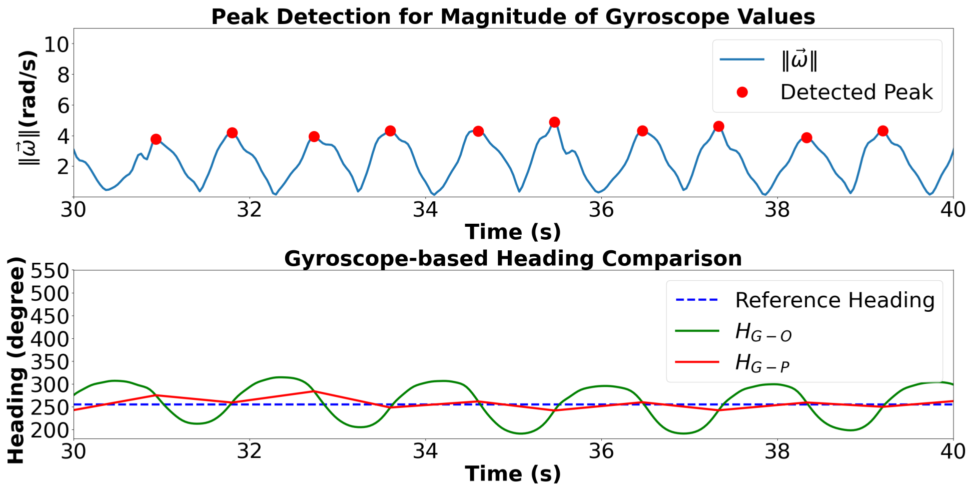

Fig. 8. The difference in heading estimation between two gyroscope-based methods.

determined at the moment when the angular velocity has the maximum value. It is the same as the PCA-based method in the earlier section for the cases of SW and PO. Figure 8 shows the comparison of the original gyroscope-based heading $H_{G\text{-}O}$ and $H_{G\text{-}P}$. It can be seen that the $H_{G\text{-}P}$ values are closer to the reference heading than the $H_{G\text{-}O}$.

E. The Selected and Adaptive Heading Estimation Method

In the beginning, it is assumed that the pedestrian keeps the smartphone in front of his body (TE) to start the application. Therefore, the initial heading from HG-P is reliable. The heading values provided in this style are considered the same as the forward walking direction of the pedestrian.

When applying the PCA-based heading $H_{PCA\text{-}P}$, the difference between two adjacent headings is sometimes large (e.g., more than 60 degrees). To solve this problem, the researchers utilize the $H_{G\text{-}P}$ from the gyroscope-based heading by replacing the current $H_{PCA\text{-}P}$ value with the current $H_{G\text{-}P}$ value as follows: IF ($H_{PCA\text{-}P}(t) - H_{PCA\text{-}P}(t-1)) > 60$) THEN ($H_{PCA\text{-}P}(t) = H_{G\text{-}P}(t)$).

Let H_{ACF} be the heading fused using the complementary filter of $H_{PCA\text{-}P}$ and $H_{G\text{-}P}$. Then, $\Delta_{PCA\text{-}P}$ and $\Delta_{G\text{-}P}$ are the differences between the current headings $H_{PCA\text{-}P}(t)$ and $H_{G\text{-}P}(t)$ with the last $H_{ACF}(t-1)$. It is shown in Eqs. (2) and (3). Then, the factor α(t) and H_{ACF} (t) are calculated using Eqs. (4)–(7). It has (t) as the latest moment (time) of the latest/current heading while ($t-1$) as the previous/last moment (time) of the previous/last heading.

$$\Delta_{PCA-P}(t) = \left|H_{PCA-P}(t) - H_{ACF}(t-1)\right|, \tag{2}$$

$$\Delta_{G-P}(t) = \left|H_{G-P}(t) - H_{ACF}(t-1)\right|, \tag{3}$$

$$\text{IF } (\Delta_{PCA-P}(t) \leq \Delta_{G-P}(t)) \text{ THEN,}$$

$$\alpha(t) = \frac{\Delta_{G-P}(t)}{\Delta_{PCA-P}(t) + \Delta_{G-P}(t)}, \tag{4}$$

$$H_{ACF}(t) = \alpha(t)H_{PCA-P}(t) + (1-\alpha(t))H_{G-P}(t), \tag{5}$$

$$\text{ELSE}$$

$$\alpha(t) = \frac{\Delta_{PCA-P}(t)}{\Delta_{PCA-P}(t) + \Delta_{G-P}(t)}, \tag{6}$$

$$H_{ACF}(t) = \alpha(t)H_{G-P}(t) + (1-\alpha(t))H_{PCA-P}(t). \tag{7}$$

The proposed method outputs different heading estimates according to the holding styles. In the case of static holding styles (TE and CA), the $H_{G\text{-}P}$ is used. Meanwhile, in the case of dynamic holding styles (SW and PO), the H_{ACF} is chosen.

TABLE II
CONFUSION MATRIX FOR FOUR HOLDING STYLES RECOGNITION.

	Error (Degree)			
	TE	CA	SW	PO
TE	1350	0	0	0
CA	0	1350	0	0
SW	0	0	1350	0
PO	0	0	0	1350

Note: Holding the smartphone in front of the pedestrian’s body for reading or texting (TE), holding the smartphone against the ears for making a phone call (CA), swinging the phone freely along the pedestrian’s walking direction (SW), and putting the phone into the pants’ front pockets (PO).

TABLE III
STATISTICAL COMPARISON OF HEADING ESTIMATION RESULTS FOR FOUR HOLDING STYLES IN THE FIRST WALKING PATH.

	Error (Degree)			
	TE	CA	SW	PO
Max.	58.89	93.12	88.49	57.68
Min.	0.07	0.04	0.15	6.84
Average	7.99	10.37	9.70	31.61
Std. Dev.	6.95	8.09	9.68	13.99

Note: Holding the smartphone in front of the pedestrian’s body for reading or texting (TE), holding the smartphone against the ears for making a phone call (CA), swinging the phone freely along the pedestrian’s walking direction (SW), and putting the phone into the pants’ front pockets (PO).

III. RESULTS AND DISCUSSION

A. Holding Style Recognition Results

To demonstrate the classification performance of the smartphone holding styles, three subjects (all males) are asked to walk around while holding the smartphone in one of four styles. The two smartphones, Samsung Galaxy S8 and Nexus 5, are used for data collection. In the training phase, for each holding style, each pedestrian walks 15 times with over 60 s walking period for each time. Thus, the total collection time is 45 times for three users and 180 times for four holding styles. Each new acceleration data (at every 1/30 seconds) is labeled with the name of one corresponding holding style during each walking period.

As mentioned, the number of selected features is only two. In the testing phase, step detection using the PDR technique was used to count the number of pedestrian walking steps. These walking steps correspond to outputs from the classifier. Each pedestrian does 15 trials with each holding style. For each trial, each pedestrian walks 30 steps. Hence, the total number of walking steps for performance analysis for three pedestrians and four holding styles is 5,400.

Table II shows the confusion matrix for four smartphone-holding styles classification. The results show that using only two features, i.e., Max_{ax} and Max_{ay}, the ET classifier can classify four holding styles with an accuracy of 100%. It means that the classifier perfectly recognizes the right holding style at every newly detected walking step.

B. The Proposed Heading Estimation Results

In this experiment, three subjects are asked to walk on two given paths. The first one is a straight walking path along a corridor in a building. Meanwhile, the second one is a rectangular walking path at a playground. The length of each walking path is 62.4 m and 306 m, respectively. The reference heading values are obtained from the GNSS to evaluate the heading accuracy of the proposed method compared to the two heading estimation methods, i.e., $H_{PCA\text{-}P}$ and $H_{G\text{-}P}$.

In the first walking path, the three pedestrians hold their smartphones in one of the four holding styles and walk in a straight path back and forth. For each holding style, each pedestrian walks on the path once, which means 3 times for each holding style and 12 times for 4

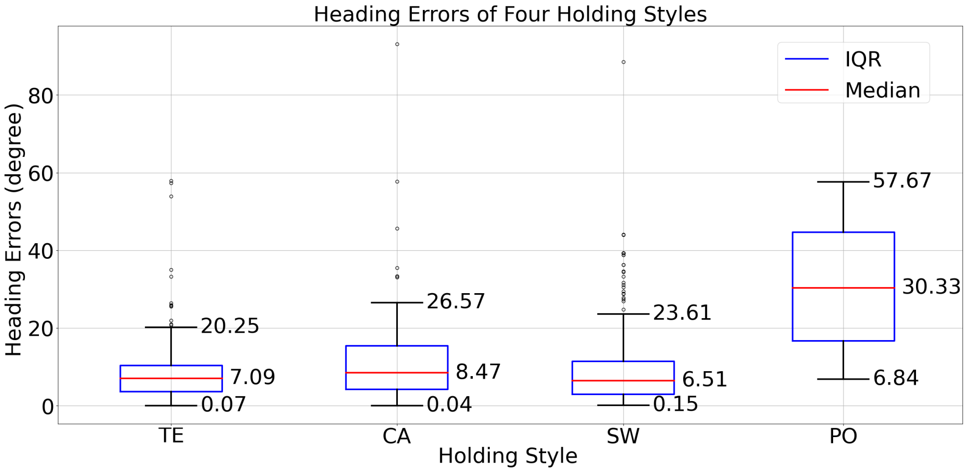

Fig. 9. Heading errors of four holding styles in the first walking path.

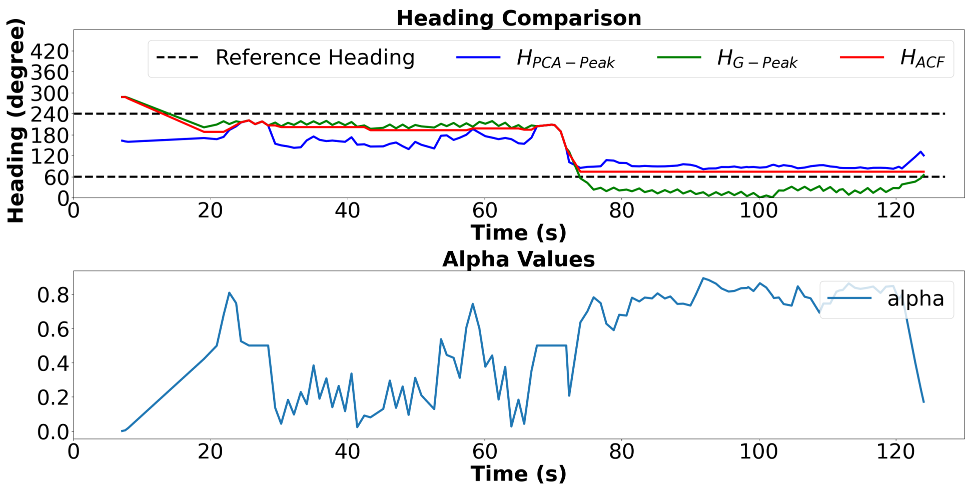

Fig. 10. Heading errors of putting the phone into the pants’ front pockets (PO) in the first walking path among three methods.

holding styles. Figure 9 shows the heading estimation result for whole holding styles using the box plot. From this figure, the performance of three holding styles (TE, CA, and SW) is quite good, with the median of heading errors being smaller than nine degrees and the 75th percentile of the errors being under 30 degrees, even though some outliers exist. Meanwhile, PO obtains the worst result since its Interquartile Range (IQR) is much bigger than others.

Table III presents the statistical analyses of heading errors for four holding styles. The mean error of TE is the lowest, while the PO has the highest mean error. The reason may be the free movement of the smartphone in the pedestrians’ pants’ front pocket during the walking period, as described previously [18].

The proposed heading estimation method, when applied to the dynamic holding styles, i.e., SW and PO, is further compared to the two headings $H_{PCA\text{-}P}$ and $H_{G\text{-}P}$. Figure 10 presents the heading results of the three methods when the pedestrian held the smartphone in PO style. From Fig. 10, the heading values estimated by the proposed method are closer to the reference heading. It is a bit better than the gyroscope-based method. Meanwhile, the PCA-based method achieves the worst result.

For deeper analysis, the Cumulative Distribution Functions (CDF) of the heading errors from the three methods are shown in Fig. 11 for the holding styles of SW and PO. For SW, the errors at the 50th percentile for $H_{PCA\text{-}P}$, $H_{G\text{-}P}$, and H_{ACF} are 19.9 degrees, 8.5 degrees, and 6.51 degrees. Then, at the 80th percentile, the errors of the three methods are 38.73 degrees, 20.68 degrees, and 13.64 degrees, respectively. Moreover, the average heading error of the proposed method for SW

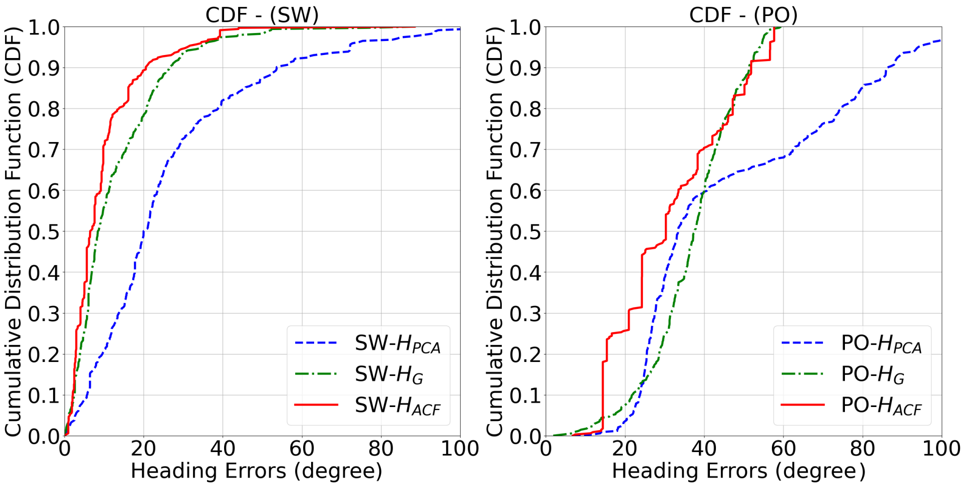

Fig. 11. Cumulative heading error distributions of swinging the phone freely along the pedestrian’s walking direction (SW) and putting the phone into the pants’ front pockets (PO) in the first walking path.

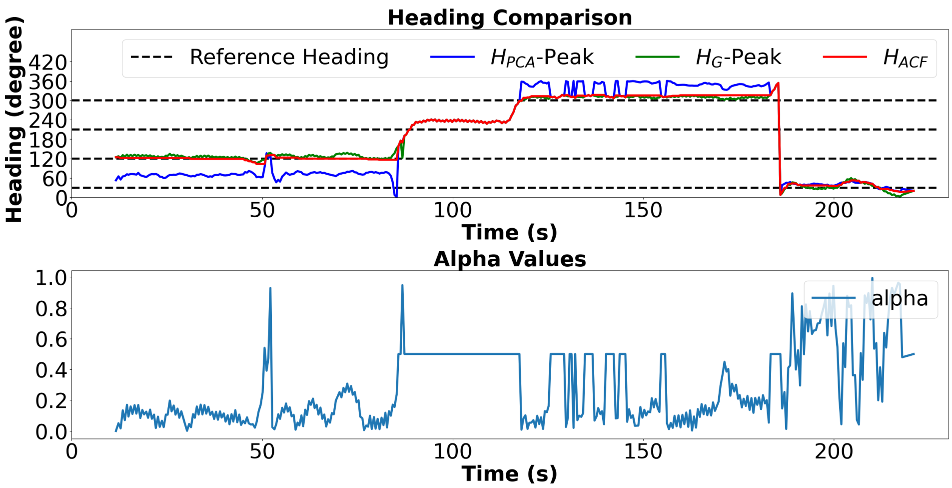

Fig. 12. Heading Errors of swinging the phone freely along the pedestrian’s walking direction (SW) in the second walking path among three methods.

is the smallest at 9.7 degrees, while these values for $H_{PCA\text{-}P}$ and $H_{G\text{-}P}$ are 25.88 degrees and 12.61 degrees. This result points out that the proposed heading estimation method reduces the errors by 23.07% to 62.52% for SW.

Moreover, for PO, the heading results are worse than SW for all three methods. However, the heading errors of the proposed method are still smaller than those of others. The average error of H_{ACF} is 31.61 degrees, which is 32.28% and 14.24% smaller than $H_{PCA\text{-}P}$ and $H_{G\text{-}P}$.

The second walking path is a rectangular walking path which is much longer than the first path to prove the robustness of the proposed method. In this experiment, only two dynamic holding styles (SW and PO) that the proposed method is applied to estimate the walking direction are considered. Three subjects are asked to walk in the rectangular path once, which means six times for the two holding styles.

Figure 12 shows the results from the three methods. The results of the proposed method H_{ACF} and the gyroscope-based method $H_{G\text{-}P}$ are quite similar and close to the reference heading. In contrast, the PCA-based heading $H_{PCA\text{-}P}$, as similar to the first walking path, gets the worst heading estimation results.

The CDF results of the three methods are pointed out in Fig. 13. For SW, the CDFs of H_{ACF} and $H_{G\text{-}P}$ are quite similar until the 75th percentile. The H_{ACF} has smaller error distributions than $H_{G\text{-}P}$ afterward. Meanwhile, $H_{PCA\text{-}P}$ still shows the worst result, with

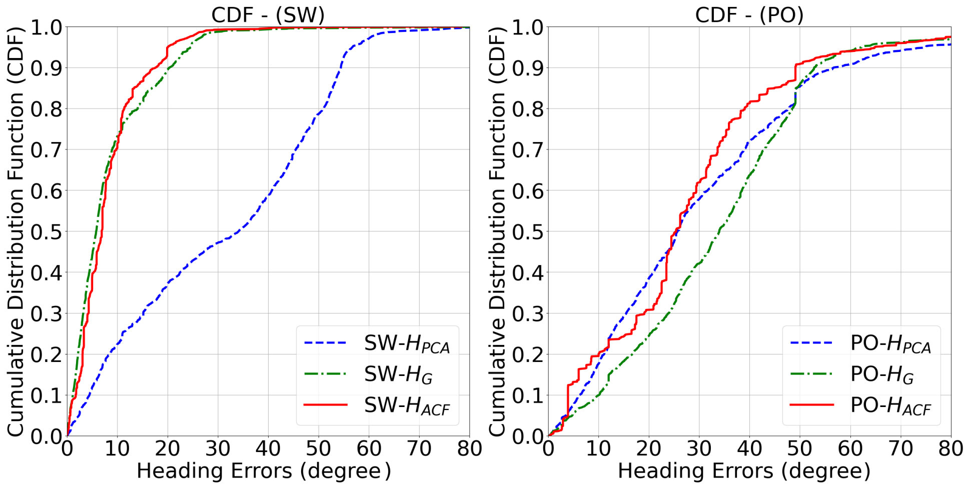

Fig. 13. Cumulative heading error distributions of swinging the phone freely along the pedestrian's walking direction (SW) and putting the phone into the pants' front pockets (PO) in the second walking path.

the error in the 80th percentile being approximately 40 degrees. For PO, the same phenomenon occurs. The proposed method still achieves the smallest heading errors. The mean heading errors of the proposed method for SW and PO are 8.13 degrees and 28.07 degrees, which reduces the errors up to 73.61% for SW and up to 17.92% for PO compared to the two other methods. When walking on a longer path, it is not easy for pedestrians to keep walking on a straight path. Hence, this situation brings the difference between the reference heading and the actual walking direction of the pedestrian. Moreover, the changing walking speed during locomotion, which changes the arm and leg movement, may affect the experimental results. At last, the different attitudes of the smartphone in the pocket also reduce the heading estimation performance.

IV. Conclusion

In the research, an adaptive heading estimation method is proposed to choose different heading estimates based on the recognized holding styles. The proposed method completely classifies four smartphone holding styles based on the ET classifier that requires only two features from the accelerometer. Then, the method calculates the heading in different ways for each holding style. For dynamic holding styles such as SW and PO, an adaptive heading estimation method is proposed to handle the dynamic changes of heading values to get more stable and accurate heading outputs. From the experiments with two different walking paths, the proposed method shows its ability to reduce heading errors compared to the two other methods. The proposed method has an average heading error of only 8.92 degrees and 29.8 degrees for SW and PO, which is 45.78% and 15.99%. Those values are lower than the PCA-based and gyroscope-based methods.

Nevertheless, the chosen threshold values and the limitation of the low-cost sensors of the smartphone may affect the stability of the heading estimation. In future research, this method can be applied to the PDR-based positioning system to verify the performance of the whole system. Moreover, various holding styles can be investigated to give pedestrians more freedom while walking.

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Author Contribution

Writing—original draft, K. N. H.; Methodology, K. N. H., and S. W. L.; Formal analysis, N. D. B., and L. N. T.; Analysis result review, L. D. T., and T. H. T. T. All authors have read and agreed to the published version of the manuscript.

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