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Smartphone Holding Styles Based Step Detection and Length Estimation*

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In this study, we propose an effective method for accurately detecting the number of walking steps and estimating the step length adaptively using the set of inertial sensors of a smartphone. The proposed walking behavior recognition method can be used as an important functional block in a pedestrian dead reckoning system. We develop a method for classifying the four main holding styles while walking, *i.e.*, holding a phone in the hand while watching it, holding a phone while calling, swinging it, and putting it in a pocket. The four main holding styles are divided into 34 sub-styles, which encompass the various free styles of holding a smartphone during daily activities. Using this holding style classification, we obtain better performance when counting the walking steps and estimating the step length, although we only employ a set of feature values that are easily calculated without any complex data processing techniques. Based on numerous experiments, we demonstrate the excellent performance of the proposed method for step counting and step length estimation for various holding styles.

Keywords: holding style recognition, pedestrian dead reckoning, smartphone, inertial sensors, indoor localization.

1. INTRODUCTION

At present, smartphones are indispensable devices in our daily lives and many applications have been developed to run on these devices to help users. Among the most helpful applications are location-based services (LBSs) that require the identification of the current location of the user and many systems have been developed for this purpose. In outdoor environments, most LBSs use global navigation satellite systems (GNSSs) such as GPS. However, we cannot use a GNSS in indoor environments. In the past decade, many studies of indoor localization have been performed but there is still no single solution that satisfies both requirements of location accuracy and the building and management costs.

Recently, many researchers have started to employ dead reckoning methods to estimate the relative rather than the absolute location of a pedestrian because these methods require little or no infrastructure in buildings and most people move around while walking. Thus, pedestrian dead reckoning (PDR) systems have been proposed in many studies as indoor localization methods. PDR systems can be categorized into two types: inertial

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navigation systems and step-and-heading systems (SHSs) [1]. SHSs estimate the position by accumulating relative changes (distance and heading) which are represented by walking steps. Naturally, SHSs need to count the number of steps and to estimate the step length and walking direction, and most SHSs employ a set of inertial sensors for this purpose. Indeed, we can obtain satisfactory results in detecting walking steps using systems with sensors attached to various body positions. However, it is still difficult to determine a user's walking direction in a global coordinates system if we do not know the exact orientation of the sensing module, especially when using a smartphone. In real situations, when a user walks, he/she holds the phone in various styles such as putting it in a pocket, watching the phone (or texting), or swaying it sideways in the hand. These various holding styles make it difficult to determine the walking direction in global coordinate system without knowing the relative orientation between smartphone and the user's body. Therefore, many SHSs assume that the orientation and holding style of the phone are known in advance [2, 3].

In order to relax these assumptions, we are developing an indoor localization system using a smartphone, which mainly employs a SHS-type PDR and a complementary radio fingerprinting method. The contributions of this study are as follows: Firstly, we describe only the PDR system of the entire system that is under development. In particular, we explain methods for recognizing holding styles, detecting the real forward walking behavior, counting steps, and estimating the step length. Secondly, we propose a method for recognizing various holding styles using a set of features obtained by various sensors in the phone. Based on the recognized holding style, our scheme attempts to detect the real forward walking behavior, to detect the number of walking step and to estimate the length of the detected step based on the step frequency and the acceleration strength.

The remainder of this paper is organized as follows. In Section 2, we briefly review related researches on indoor localization methods. Section 3 provides detailed descriptions of the proposed methods. The experimental results are presented in Section 4. In Section 5, the conclusions and suggestions for future research are given.

2. RELATED WORK

There have been many previous surveys of indoor localization systems. Hightower and Borriello [4] provided a taxonomy of various location-sensing systems for location-aware applications. Liu [5] also gave an overview of wireless indoor positioning solutions and attempted to classify them, where they summarized three typical techniques for triangulation, scene analysis, and proximity, as well as discussing location fingerprinting in detail. Recently, Harle [1] presented a taxonomy of modern PDR systems and reviewed various techniques for step detection, inertial navigation, and SHS-based dead reckoning, where it was concluded that the PDR technique alone can facilitate good short- to medium-term tracking.

The detection of steps or strides is an important task for SHSs. Most of the detection algorithms are threshold-based, where they employ the acceleration magnitude [6], angular velocity [7], or their combination [8]. Various step detection methods that use non-inertial sensors have also been suggested, including pressure sensors embedded in the sole of the shoe [9] and ultrasonic ranging between the feet [10]. In fact, detecting a step cycle using sensors placed on parts of the body is not simple or reliable.

Estimating the step length or stride length is also important for a SHS because the positional change in one step is computed directly from the step length. Fortunately, pedestrians walk naturally with a surprisingly constant step length. Thus, many PDR systems use a constant step length. However, this natural walking pace often varies in different situations. Weinberg reported that the step length can vary by as much as 40% between people walking at the same speed [11]. He also proposed a dynamic step length estimation method based on the strength of acceleration in the vertical direction. Some studies [12, 13] have reported that there is a linear relationship between the step frequency and the step length; thus, a combined method that employs both properties is proposed.

The widespread deployment of appropriate sensors in smartphones is one of the key motivations for employing PDR. Smartphone-based PDR systems are highly attractive, but they present new difficulties by loosening the attachment constraints. Some researchers have assumed that the smartphone is attached to the waist [14], or held in the hand [15]. In a previous study [16], instead of assuming that smartphone has attached to the fixed part, we tried to estimate the holding style as in the present study. Recently, Kang *et al.* [17] proposed a full indoor localization system based on a smartphone kept on hands all the time to track the position of pedestrian on the application interface.

Additional communication capacities of smartphones have been focused on in the development of hybrid methods. The most popular hybrid systems combine PDR with WiFi fingerprinting to overcome the limitations of both. Woodman simplified the data collection problem using an SHS and particle filtering method [18]. The Zee system [19] achieves location recognition by WiFi fingerprinting, as well as by making a radio map that is crowd-sourced from the users with SHS-capable smartphones.

3. PROPOSED METHOD

3.1 System Overview

Fig. 1 shows a block diagram of our indoor localization system, which comprises two main systems: a PDR system and a WiFi fingerprinting-based localization system. In this study, we only consider the PDR system.

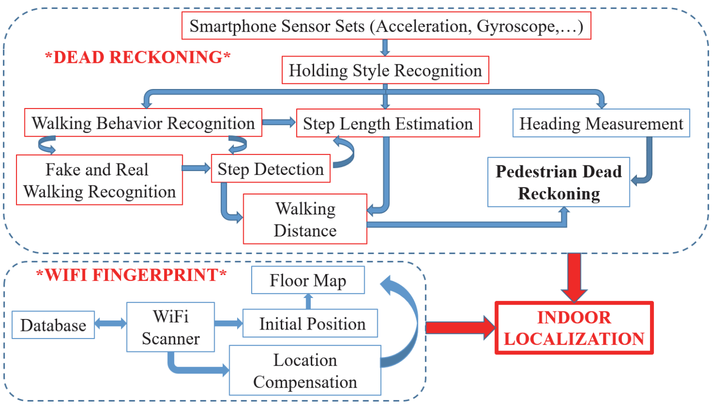

Fig. 1. Block diagram of the overall indoor localization system.

In the first step, we use sets of sensor data to classify the smartphone holding styles since we assume that estimating the holding style can be very helpful for a PDR system. After determining the holding style, we try to recognize the walking behavior. For this step, we propose a novel method that discriminates fake and real walking forward behaviors by using the combination of accelerometer and magnetometer on smartphone. If the system detects that the current behavior is actually forward walking, then the method tries to count the number of walking steps. Whenever a new step is determined, the system estimates the length of the current step based on its cadence and the user's physical features, such as their height. Thus, we propose an estimation method which uses the cadence and the strength of acceleration to estimate each step, thereby allowing us to determine the relative moving distance from the previous position. Next, the PDR system requires information about the walking direction. Sensing a user's global walking direction is a very important and challenging problem in real life situations because the phone is held in different orientations at various body positions. Many previous studies have assumed that the system knows the orientation of the sensing module (*i.e.*, phone) or even the walking direction. Our system estimates the user's walking direction more accurately and stably by recognizing the holding style [20]. However, in this study, we only describe the methods for obtaining the distance information, which include the step detection method and step length estimation method.

The other main component of our localization system is a conventional WiFi fingerprinting system [21]. We employ the WiFi fingerprinting system to estimate the initial position and/or to eliminate the accumulated error in a PDR system by using a relatively small numbers of reference points compared with conventional fingerprinting systems. When a new step is found, the scheme scans the WiFi signals to determine the current location among the pre-determined reference positions. The main aim of our full study is to enhance the complementary performance of the PDR and radio fingerprinting techniques.

Table 1 summarizes the various notations and symbols which will be used in this paper.

Table 1. Notations and symbols.

Notation	Definition
HA	Holding the phone in the hand for texting or watching
CA	Holding the phone parallel to the ear while making a call
SW	Swinging the phone while walking
PO	Placing the phone into a pocket
ω_x, ω_y, ω_z	The x, y, z components of the gyroscope vector (rad/s)
g_x, g_y, g_z	The x, y, z components of the gravity vector (m/s^2)
la_x, la_y, la_z	The x, y, z components of the linear acceleration vector (m/s^2)
m_x, m_y, m_z	The x, y, z components of the magnetic vector (μT)
$\|\|\overrightarrow{\omega_v}\|\|$	The magnitude of the gyroscope vector (rad/s)
E_β	The pitch angle of the orientation sensor (degree)
Touch	The status whenever the user touches the screen while texting
prox	The output of a proximity sensor (cm)
light	The output of a light sensor (lux)
$\mu_{g_{xy}}$	Mean value of the x and y components of the gravity vector (m/s^2)

$\mu_{g_x,30}$	The average value of the previous 30 samples of the x component of the gravity vector (m/s^2)
$\max_{\omega_x,30}$	The maximum value among the last 30 samples of the x component obtained from the gyroscope vector (rad/s)
$\sigma_{g_z,60}$	The standard deviation of the last 60 samples of the z component of gravity vector (m/s^2)
$\sigma_{\omega_x,20}$	The standard deviation of the last 20 samples of the x component of the gyroscope vector (rad/s)
$\sigma_{\lvert\vec{\omega}\rvert,12}$	The standard deviation of last 12 samples of the magnitude of the gyroscope vector (rad/s)
$\mu_{g_x,30}$	The average of the last 30 samples of the x component of gravity vector (m/s^2)
$\mu_{g_z,30}$	The average of the last 30 samples of the z component of gravity vector (m/s^2)
$\sigma_{\lvert\vec{m}\rvert,12}$	The standard deviation of the last 12 samples of the magnitude of the magnetic vector (rad/s)
$S_{\lvert\vec{la}\rvert}$	The sum of the last 12 samples of the magnitude of the linear acceleration vector (m/s^2)
f_{fw}	The fusion feature from $\sigma_{\lvert\vec{m}\rvert,12}$ and $S_{\lvert\vec{la}\rvert}$
$\sigma_{f_{fw},12}$	The standard deviation of the last 12 samples of the fusion feature f_{fw}
$\mu_{\sigma_{fw}}$	The average of the last four values of $\sigma_{f_{fw},12}$
$p^{(+)}$	The positive peak of the selected input signal (m/s^2 for the linear acceleration vector or rad/s for gyroscope vector)
$p^{(-)}$	The negative peak of the selected input signal (m/s^2 for the linear acceleration vector or rad/s for gyroscope vector)
$t_{p^{(+)}}$	The moment when $p^{(+)}$ is detected
$t_{p^{(-)}}$	The moment when $p^{(-)}$ is detected

3.2 Holding Style Estimation

The holding style is defined as how a user holds his/her smartphone. During our daily life, we may hold the phone in many ways while walking, such as swinging it along beside the leg, watching the screen, or making a call. In this study, we selected four holding styles that represent typical styles employed in daily activities such as: holding the phone in the hand for texting or watching (**HA**), holding the phone parallel to the ear while making a call (**CA**), swinging the phone while walking (**SW**), and placing the phone into a pocket (**PO**), as shown in Fig. 2.

For each holding style, the user can also hold his/her phone in many different ways. For example, for the style (**CA**), the user may hold it in the right or left hand. In addition, the orientation of the phone may differ depending on how the phone is grabbed. Thus, we determined many possible sub-cases for each holding style, *i.e.*, four main holding styles and 34 sub-cases of them, as shown in Fig. 3, where the holding styles are categorized according to a hierarchical structure. The estimator inevitably decides 34 holding styles even if smartphones are used with other holding styles.

Fig. 2. Four main holding styles.

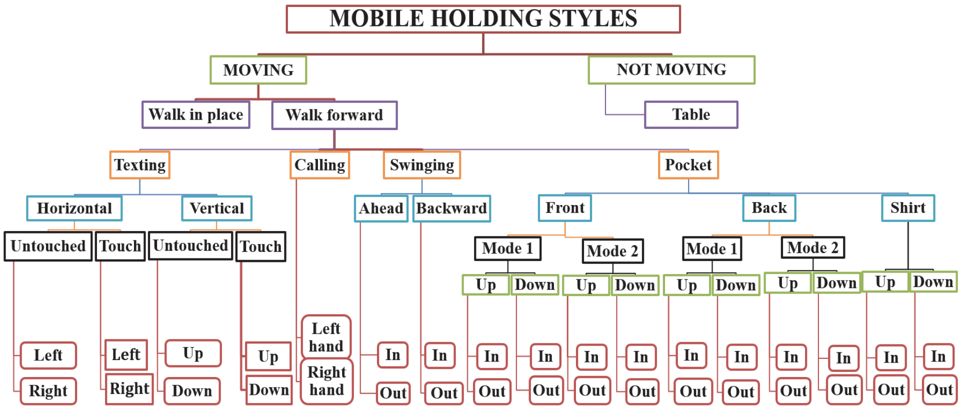

Fig. 3. All the estimated holding styles.

We propose a simple but effective recognition method for classifying the 34 holding styles using various sensor signals. The main sampling frequency is 30 Hz. At each sampling time, the holding style estimator reads the output signals from the sensors, *i.e.*, the gyroscope, proximity, and light sensors, and the software sensors provided in Android system, *i.e.*, the gravity and the orientation sensors. The phone tries to estimate the current holding style using the calculated feature values with various thresholds at each sampling time. The thresholds in this paper are determined empirically. However, the system determines the final holding style when a new walking step is detected because the position should be updated at every new step in a PDR system. The "Changing Style" class is added to determine whether the smartphone position has changed from one holding style to another. The "Changing Style" is classified when the magnitude ($\|\vec{\omega}_v\|$) of the gyroscope vector, $\vec{\omega}_v = (\omega_x, \omega_y, \omega_z)$, is greater than a threshold Th_1. Th_1 in this case is 1 rad/s. The proposed system keeps the recognized holding style if the condition of "Changing Style" is not satisfied. For the style (**HA**), the y component (g_y) of the gravity vector, , $\vec{g}_v = (g_x, g_y, g_z)$ and the pitch angle (E_β) of the orientation sensor are used. When the smartphone is in (**HA**), we can easily recognize the orientation of the phone among the vertical (*i.e.*, portrait) direction ("Up/Down" notations in Fig. 3) and horizontal (*i.e.*, landscape) direction ("Left/Right" notations). The "**Touch**" function is added for (**HA**) to indicate the status whenever the user touches the screen while texting. For the style (**CA**), we use the output of a proximity sensor (abbreviated as **prox**) and the two components of the gravity vector: g_x, g_y. When the smartphone is near the ear, (**prox**) changes greatly with positive values of g_x, g_y for the "left hand" and negative values for the "right hand." The style (**PO**) shows that $g_y < 0$ and the output of a light sensor (abbreviated as **light**) < Th_2 (Th_2 = 10 *lux*). In particular, during the second stage in (**PO**), we discriminate the smartphone in the front pockets of the pants according to two statuses: placed in the pocket with the screen pointing inward or outward compared with the body, where we use g_z. If $g_z < 0$, then the screen points inward and vice versa for the outward direction. Furthermore, when the smartphone is placed into the pocket in an upward direction, it has a similar orientation to the style (**CA**), so we use a new feature given by the following equation:

$$\mu_{g_{xy}} = \frac{g_x + g_y}{2}. \tag{1}$$

We find that $\mu_{g_{xy}} \leq Th_3$ for the style (**CA**) and $\mu_{g_{xy}} \leq Th_3$ for the style (**PO**). The sub-cases of "Up/Down" can be recognized easily using g_y. The value of Th_3 is 3 m/s^2. For the style (**PO**), we find that the phone may be located in different positions if the size of the pocket is large, as shown in Fig. 4. We denote these differences in terms of mode 1 and 2. To discriminate these positions, we use the average value of the previous 30 samples of the x component of the gravity vector, as follows:

$$\mu_{g_{x,30}} = \sum_{i=1}^{30} \frac{g_x(t-i)}{30} \tag{2}$$

where t is the current sampling time. The previous samples are stored in a moving window of 30 samples, *i.e.*, a period of around 1s. The feature $\mu_{g_{x,30}}$ has a bigger value in mode 1 than mode 2.

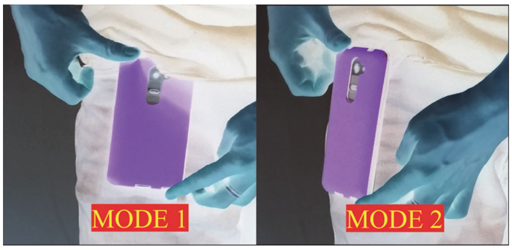

Fig. 4. Different locations of a phone in a pocket.

Next, the estimator tries to classify the style (**PO**) more specifically among four sub-cases: placing into the front pocket of pants, back pocket of pants, shirt pocket, or the pocket on a backpack. A backpack is an additional sub-case because many people keep their smartphone in a backpack while walking. To differentiate the shirt and the front of pants, we determine the maximum value (denoted as $\max_{\omega_{x,30}}$) among the last 30 samples of the x component obtained from the gyroscope, ω_x. Placing a phone in the pocket of a shirt has a smaller $\max_{\omega_x,30}$ value. Two features are added to classify the four pocket style sub-cases. One feature is the standard deviation of the last 60 samples of the z-component of gravity, which is denoted as $\sigma_{g_z,60}$, and the other is the standard deviation of the last 20 samples of the x-component obtained from the gyroscope, which is denoted as $\sigma_{\omega_x,20}$. We summarize these classification conditions in Table 2 with $Th_4 = 1.5$ and $Th_5 = 0.6$.

To classify the style (**SW**), we use the standard deviation (denoted as $\sigma_{|\vec{\omega}|,12}$) of last 12 samples of the magnitude of the gyroscope vector, *i.e.*, $\|\vec{\omega}_v\|(t-i)$, $i = 1, 2, \ldots, 12$. If $\sigma_{|\vec{\omega}|,12} > Th_6$, then the system determines the style (**SW**), where the user keeps their phone in hand in landscape and they swing it while walking. Th_6 is chosen as 0.5. For the style (**SW**), there are four sub-cases depending on how the phone is grabbed: swing ahead and inward, swing ahead and outward, swinging backward and inward, swinging backward and outward. The inward/outward distinction represents the direction of the screen and ahead/backward denotes the direction of the top of the phone. We use two features to classify these four sub-cases for (**SW**): the average of the last 30 samples of the x-component of gravity, $\mu_{g_x,30}$, and the average of the last 30 samples of the z-component of gravity, $\mu_{g_z,30}$. Table 3 shows the conditions for these feature values with $Th_7 = Th_8 = 0$ m/s^2. Table 4 summarizes all of the features used to classify the different holding styles.

Table 2. Classification conditions for four sub-cases of the style (PO).

Cases	$\sigma_{g_z,60}$	$\sigma_{\omega_x,20}$
Pocket of shirt	$\le Th_4$	$\le Th_5$
Front pocket of pants	$> Th_4$	$> Th_5$
Back pocket of pants	$\le Th_4$	$> Th_5$
Pocket of backpack	$> Th_4$	$\le Th_5$

Table 3. Classification conditions for four sub-cases of the style (SW).

Cases	$\mu_{g_x,30}$	$\mu_{g_z,30}$
Swing ahead inward	$> Th_7$	$\le Th_8$
Swing backward inward	$\le Th_7$	$\le Th_8$
Swing ahead outward	$\le Th_7$	$> Th_8$
Swing backward outward	$> Th_7$	$> Th_8$

Table 4. Summary of the features used to estimate different holding styles.

		Feature (15)														
		(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)	(m)	(n)	(o)
1	HA	●	●	●	●			●						●		Changing Style
2	CA	●	●			●					●					
3	SW	●	●	●					●	●			●	●		
4	PO		●	●			●		●	●		●	●		●	

where letters a-o are g_x, g_y, g_z, E_β, prox, light, Touch, $\mu_{g_x,30}$, $\mu_{g_z,30}$, $\mu_{g_{xy}}$, $\max_{\omega_x,30}$, $\sigma_{g_z,60}$, $\sigma_{|\vec{\omega}|,12}$, $\sigma_{\omega_x,30}$, $\|\vec{\omega}_v\|$, respectively.

3.3 Walking Behavior Recognition

The recognition of walking behavior is essential for a PDR localization technique because the number of walking steps detected determines the walking distance. Thus, we aim to discriminate a forward walking behavior from similar behaviors such as walking on the spot. When a user walks on the spot (referred to as “fake walking”), if the smartphone recognizes this as a new walking step, the system will update the position of the user incorrectly. In order to solve this problem, we propose a simple method that uses two features: the standard deviation of the last 12 samples, which represents the magnitudes of the vectors of the magnetic sensor signals, $\sigma_{|\vec{\omega}|,12}$, $\vec{m} = (m_x, m_y, m_z)$, and the sum of the last 12 samples of the magnitude of the linear acceleration vector by the following equation:

$$S_{|\vec{la}|}(t) = \sum_{i=1}^{12} K \left\| \overrightarrow{la(t-i)} \right\| \tag{3}$$

where K is a scaling factor and $\|\overrightarrow{la(t)}\|$ is the magnitude of the linear acceleration vector $\vec{la} = (la_x, la_y, la_z)$.

When a user walks forward, $\|\vec{m}\|$ will vary greatly compared with that when a user walks on the spot; thus, we employ this as the first feature. The second feature has a similar property. Thus, when a user walks forward, $S_{|\vec{la}|}$ will change greatly. The two features are plotted in Fig. 5, which clearly demonstrate the differences between these features during real and fake walking behaviors.

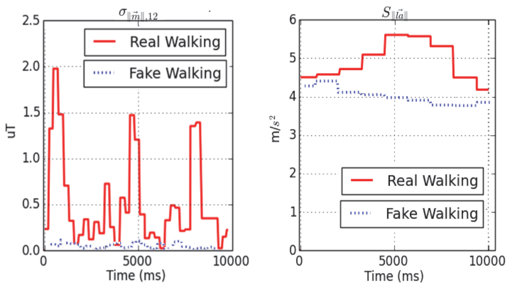

Fig. 5. Two features used for discriminating real and fake walking.

To make the results clearer, we introduce a new feature, $f_{fw}(t)$, which is computed by fusing the two features described above. We use the complementary filter technique for fusion according to the following equation:

$$f_{fw}(t) = \alpha \sigma_{|\vec{m}|,12}(t) + (1-\alpha) S_{|\vec{la}|}(t) \tag{4}$$

where α is the filter coefficient and in this work $\alpha = 0.8$. At each sampling time, the fusion feature $f_{fw}(t)$ is calculated and saved in a buffer. Our scheme then computes the standard deviation ($\sigma_{f_{fw},12}(t)$) for the last 12 samples of the $f_{fw}(t)$. Finally, we calculate the average $\mu_{\sigma fw}(t)$ using the last four values of the standard deviation value, $\sigma_{f_{fw},12}(t-i)$, $i = 0, \ldots, 3$. Fig. 6 shows the trajectories of the feature $\mu_{\sigma fw}(t)$ for the real and fake walking behaviors, which clearly demonstrates the differences between the two walking behaviors.

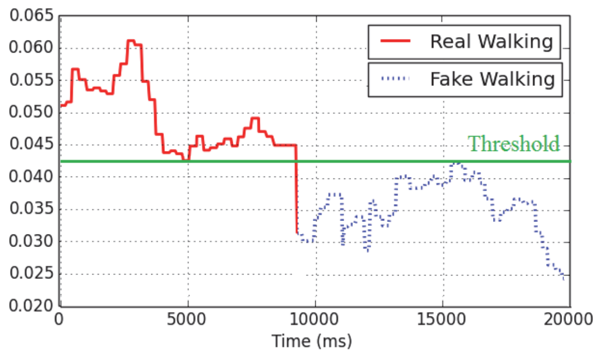

Fig. 6. Trajectories of the averaged fused feature values for real and fake walking.

We use different threshold values based on the estimated holding style to improve the recognition accuracy. For the holding styles (**HA**, **CA**), if $\mu_{\sigma fw}(t) > Th_9$, where Th_9 is 0.025, then our scheme determines that the current behavior is real walking; otherwise, it is fake walking. For the holding styles (**SW**, **PO**), we compare $\mu_{\sigma fw}(t)$ to the different threshold value Th_{10} which is 0.043. We can obtain more accurate recognition results by using different threshold values. In case of (**HA**, **CA**), the smartphone does not move (changing position in compared with the user's body) a lot while walking, but in case of (**SW**, **PO**), the smartphone moves violently and periodically. Therefore, the (**HA**, **CA**) will be assigned the same threshold and (**SW**, **PO**) will be assigned another threshold.

3.4 Step Detection

Whenever the system detects real walking behavior, it executes the step counting method. The proposed method also uses the estimated holding style to ensure more stable and accurate detection. The relationship between the sensor signals and walking behavior depends on the holding style. For example, if a user holds their smartphone in styles (**HA**) and (**CA**), we focused on the moment of heel strike so we have chosen the magnitude of the linear acceleration vector ($\|\overrightarrow{la(t)}\|$) because it exhibits better repeatability than the magnitude of the gyroscope vector ($\|\overrightarrow{\omega(t)}\|$). By contrast, for the holding styles (**SW**) and (**PO**), the motion of device includes more rotational movements than linear movements, so it is easier to use the magnitude of the gyroscope vector to detect the walking steps. Therefore, the input signals employed to detect the step are linear acceleration values for holding styles (**HA**) and (**CA**), and gyroscope values for holding styles (**SW**) and (**PO**). During one gait cycle, there are always two phases: stance and swing. During the swing phase, we can easily find the positive peak (maximum – $p^{(+)}$) and the negative peak (minimum – $p^{(-)}$) of the selected input signal, such as the magnitude of linear acceleration and the gyroscope vector across all holding styles. The system tries to find the positive and negative peaks, and the two moments: $t_{p^{(+)}}$ moment ($p^{(+)}$ occurs) and $t_{p^{(-)}}$ moment ($p^{(-)}$ occurs). If the system detects all of these features, then two conditions are checked: the magnitude of the difference between positive and negative peaks, *i.e.*, $(p^{(+)} - p^{(-)}) > Th_{11}$, and the time interval between the two moments: $Th_{12} \leq (t_{p^{(+)}} - t_{p^{(-)}}) \leq Th_{13}$. If these conditions are satisfied, then one new step is detected. In these conditions, Th_{11} is different for each holding style: 0.15 m/s^2 for (**HA**), 0.05 m/s^2 for

(**CA**), 0.8 rad/s for (**SW**) and 0.94 rad/s for (**PO**); $Th_{12} = 3$ and $Th_{13} = 12$. The thresholds differ among holding styles since in each holding style, the input data differs from the sensors (linear acceleration and gyroscope), thus their magnitude ranges are also different. The time interval represents the walking speed so we can check whether it is within the possible walking speed range.

3.5 Step Length Estimation

During the human gait cycle, the step length is defined as the distance between the corresponding successive heel contact points of the opposite feet. We propose an estimation method that uses two walking behavior properties that affect the step length: the cadence and the strength of acceleration. The cadence is defined as the number of steps per unit time, which means that the cadence is greater when a person walks faster.

With body fixed sensors and even with handheld devices, there exists a linear relationship between step length and cadence of a user: if the user walks faster, both the step length and the cadence increase [22, 23]. Moreover, the user's step length is proportional to the length of the user's height [24]. Because of these reasons, based on both the cadence and the height of a user, we can calculate the step length of that one. The step length can be calculated from the first property by the following equation:

$$SL_1(n) = K_{S1} h_j f_S(n), f_S(n) = 1/|t_{p^{(+)}} - t_{p^{(-)}}| \tag{5}$$

where K_{S1} is a calibration constant which is different for each individual, h_j is the height of user j and $f_S(n)$ is the inverse of the time interval of the moments of two peaks for the nth step, which represents a cadence factor. The other step length method is computed based on the strength of acceleration in a similar manner to the method of Weinberg [11]. There is an empirical relationship between the vertical input signals (acceleration, gyroscope, *etc.*) with the stride length [1] so that this method assumes that the step length is proportional to the vertical movement of the human hip, where the hip bounce is estimated from the largest acceleration differences during each step. Another component is also introduced to consider this property by using the two peaks as:

$$SL_2(n) = K_{S2} \sqrt[4]{p^{(+)} - p^{(-)}} \tag{6}$$

where K_{S2} is a calibration constant, $p^{(+)}$, $p^{(-)}$ are the positive and negative peaks of the nth step of input signal, respectively. After doing experiments and comparing with other comparable combinations (arithmetic and geometric means) with two components, we propose a method for calculating the length of the nth step with these two components as follows.

$$SL(n) = K_{S3} \sqrt{(SL_1(n))^2 + (SL_2(n))^2} \tag{7}$$

where K_{S3} is a calibration constant.

The scaling constant $K_{S[1,2,3]}$ will be different values depending on the recognized holding style.

4. PERFORMANCE EVALUATION

4.1 Experimental Setup

As shown in Fig. 7, all experiments were executed in three scenarios with five users (all males with heights ranging from 1.62m to 1.80m). The experiments were conducted in 3rd floor of Engineering Building at Hallym University. In scenario 1, we tested the performance of our method in a small area where there was noise from many electrical devices (unstable environment) as a typical laboratory environment. In scenario 2, the users walked in a straight line down a long corridor to assess the performance in a longer and more stable environment. In scenario 3, the performance was tested by combining the two scenarios described above, where the users walked in different environment conditions, which ranged from unstable to stable environments. The true distance is defined as the length of the given path the user walks. It was measured manually by using the measuring tool named "Walking Measure", Model: WM-1K (Made in Japan).

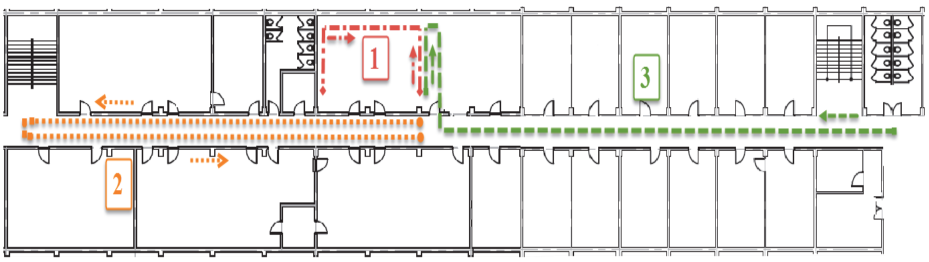

Fig. 7. Walking paths in the three test scenarios.

4.2 Holding Style Estimation Results

To estimate the smartphone holding style, the five users held their smartphones while walking in five situations that corresponded to the four holding styles, *i.e.*, (**HA**), (**CA**), (**SW**), and (**PO**), and a random mixture of all of them. For each holding style, each user walked the path two times, *i.e.*, there were 10 trials replicated for each scenario and 150 for five users in three scenarios. The system recognized the holding style when a new walking step was detected. Thus, the number of holding styles recognized was the same as the number of steps detected. We evaluated the accuracy of holding style recognition in discrete samples.

Table 5 shows the confusion matrix for the experimental results when we tested each holding style separately in three scenarios. Each row shows the recognized holding

Table 5. Recognition results in separate holding style trials.

	Holding Style	HA	CA	SW	PO	Error rate (%)
Recognized	HA	2784	0	0	0	0.43
	CA	0	2574	0	0	0
	SW	104	0	2610	0	3.83
	PO	15	0	35	2638	1.86

styles result. For example, at the row of (PO), the scheme exactly recognized the smartphone was in the pants' pocket 2638 times and got 35 times recognized as (SW) and 15 times as (HA). Therefore, the error rate of (PO) is 1.86%. The overall results were good for the holding styles, where the error rate ranged from 0% for style (**CA**) to 3.83% for (**SW**). The average error rate for the separate holding styles in three scenarios was only 1.54% (166 steps) among 10,772 steps in total for all trials.

Table 6 shows the results when we allowed the users to change their holding styles freely while walking in all of the scenarios. For mixed holding styles, the lowest and highest error rates were 1.31% for style (**HA**) and 2.94% for style (**SW**). Among the total of 2,734 steps, we detected only 52 errors, and thus the average error rate was 1.9%. Therefore, we obtained very good recognition performance even when the users changed their holding style freely while walking. According to the error analysis, our scheme did not perform well at recognizing the moment of step detection when it was close to the middle of changing the holding style, thereby leading to errors.

Table 6. Recognition results obtained in the mixed holding style trials.

Mixed Holding Style		HA	CA	SW	PO	Error rate (%)
Recognized	HA	977	0	9	4	1.31
	CA	2	769	10	0	1.54
	SW	10	5	496	0	2.94
	PO	3	0	9	2638	2.65

4.3 Step Detection Results

In order to evaluate the walking step detection performance using the proposed method, we designed a set of experiments based on five users, four holding styles, and the three previous scenarios. Each user walked four times using each holding style, *i.e.*, 20 times for each scenario and 300 times for five users in three scenarios. The experimental results are summarized in Table 7.

Table 7. Results of the step detection.

Holding Style	Detected steps	Error steps	Error rate (%)
HA	5731	114	1.99
CA	5161	108	2.09
SW	5197	87	1.67
PO	5472	112	2.05
Mixed	5672	77	1.35
Sum	27233	498	1.83

The error steps were computed as absolute values because the method could count them not as real steps (overestimate) or as real steps (underestimate). According to Table 7, the lowest error rate was 1.35% and the highest was 2.09%, while the average error rate was 1.83%. These results show that the proposed method performs sufficiently well for use in PDR localization. The most errors occurred when detecting the first step while walking because our method could not find appropriate peaks to meet the given conditions. In some cases, the counts were overestimated when a user stopped abruptly because of the inertial force effect. We aim to remove these limitations by using new combinations of inputs from other sensors.

4.4 Step Length Estimation Results

The step length estimation results were calculated from the data sets collected in the same experiments, as explained in the previous section. Thus, five users walked in three scenarios using four holding styles, where each case was executed four times by each user, *i.e.*, each user walked 20 times along the path in each scenario. We asked the users to walk freely at different speeds, *i.e.*, slow, normal or fast speed. The total lengths of the paths in the three scenarios were 607m, 1580m, and 2152m, respectively. The scaling constant K_{S3} is 0.15 for the styles (**HA**)/(**CA**) and 0.25 for (**SW**)/(**PO**).

The results of the proposed method (Eq. (7)) in three scenarios are shown in Table 8, where the error distances in the table are also the absolute values because the distance calculated from the smartphone could be lower or higher than the true distances that the users walked. The highest error rate was 7.38% for holding style (**SW**) in scenario 1 and the lowest was 2.35% for style (**PO**) in scenario 3. The average error distances and rates in the three scenarios were 27.55m (4.53% over 607m), 43.7m (2.75% over 1,580m), and 58.29m (2.73% over 2,152m), respectively. The overall average error rate was 3.34% for an average path length of 1,446.3m. As expected, the largest error distance was obtained for the longer path. We consider that the performance of the proposed estimation method was promising even when the users changed their walking speed freely.

Table 8. Results of the step length estimation.

Holding Styles	Scenario 1		Scenario 2		Scenario 3	
	Error (m)	Error (%)	Error (m)	Error (%)	Error (m)	Error (%)
HA	28.27	4.66	31.19	1.97	51.56	2.40
CA	21.68	3.57	44.22	2.80	52.9	2.46
SW	44.79	7.38	38.48	2.44	82.54	3.84
PO	20.6	3.39	61.17	3.87	50.59	2.35
Mixed	22.41	3.69	43.44	2.75	53.85	2.50
Mean	27.55	4.53	43.7	2.75	58.29	2.73

To further assess the performance of our proposed method, we compared the results obtained with those produced using the Weinberg method as in Eq. (6) and constant step length methods. We used the basic idea rather than the original Weinberg method to facilitate a simple and fair comparison. The different signals used to find the peaks depended on the estimated holding style, as described in the previous section. The scaling constant K_{S2} is 0.55 for the styles (**HA**)/(**CA**) and 0.57 for (**SW**)/(**PO**). The proposed method used the height information for each user. Thus, we calculated the set of results using three constant lengths for one step, as follows:

$$SL_{C1} = 0.42h_j, SL_{C2} = \begin{cases} 0.415h_j, & \text{man} \\ 0.413h_j, & \text{woman} \end{cases}, SL_{C2} = \begin{cases} 0.78m, & \text{man} \\ 0.70m, & \text{woman} \end{cases}, \tag{9}$$

where h_j is the height of the user and the constants were selected from [25]. The results obtained in the three scenarios are shown in Tables 9, 10, and 11, which demonstrate that the errors obtained using our proposed method were much smaller in all of the scenarios compared with those with all of the other methods. We also found that the variation in the error was smaller using our method compared with the others based on the lower standard deviations. The maximum error distance using our method was 7.19m for the longest path (scenario 3) compared with a value of 33.87m using the Weinberg method. The minimum error distance was 0.01m compared with 0.14m when using SL_{C1}.

Table 9. Step length estimation errors in scenario 1.

	Proposed method	Weinberg method	SL_{C1}	SL_{C2}	SL_{C3}
Mean (%)	4.66	6.62	5.32	5.97	7.42
Std. dev. (%)	2.84	5.91	2.87	3.11	5.41
Max (m)	2.71	7.34	3.62	3.94	4.75
Min (m)	0.3	0.22	0.36	0.46	0.71

Table 10. Step length estimation errors in scenario 2.

	Proposed method	Weinberg method	SL_{C1}	SL_{C2}	SL_{C3}
Mean (%)	1.97	26.65	8.83	9.92	4.35
Std. dev. (%)	1.68	5.75	3.06	3.02	3.21
Max (m)	4.67	23.9	11.17	11.98	8.02
Min (m)	0.08	11.05	3.15	4.05	0.56

Table 11. Step length estimation errors in scenario 3.

	Proposed method	Weinberg method	SL_{C1}	SL_{C2}	SL_{C3}
Mean (%)	2.40	24.58	5.92	7.04	4.07
Std. dev. (%)	1.91	3.70	2.46	2.43	3.54
Max (m)	7.19	33.87	10.53	11.69	7.11
Min (m)	0.01	20.12	0.14	1.41	0.69

In comparison with a recent work in [17], their average location error is 1.35m in total length of 168.55m with the accuracy is 99.2%, whereas we have the average errors as 27.55m, 43.7m and 58.29m for three difference scenarios in total lengths of 607m, 1580m and 2152m with the accuracies are 95.5%, 97.23% and 97.29%. Although our average error distance is higher than in their method, our method can cover four different holding styles with reasonable results rather than their only one holding style.

5. CONCLUSIONS

In this study, we proposed a method for tracking the position of users while they hold their smartphone in various holding styles in an indoor environment. The proposed method classifies four main holding styles which are divided into 34 sub-cases, discriminates real walking behavior from fake walking behavior, counts the number of steps during real walking, and estimates the length of each step. Our method aims to find appropriate features that do not incur high computational costs while still achieving high accuracy. In future research, we will address two main issues: enhancing the performance of the proposed methods to obtain a better PDR system, and developing a combined indoor localization system based on a PDR system and a WiFi fingerprinting system. Moreover, we want to develop a more systematic method for tracking the motion of a smartphone user while he/she walks. We are investigating different ways of using WiFi fingerprinting techniques to make our PDR system more cost-effective and useful for indoor localization systems.

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