Pedestrian Dead Reckoning for Multiple Walking Styles Using Classifier-Based Step Detection

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***Abstract*—Traditional pedestrian dead reckoning (PDR) systems have been designed for scenarios where users walk straight ahead. However, user behavior observation at the museum revealed that users often stop or walk sideways to look at the exhibits. If the user's smartphone is moving when the user is stopped, false step detection may occur. In addition, the correct step or change of direction may not be detected in sideways walking. To solve these problems, we propose a novel PDR system. First, we classify the user's walking style to address the problems of false step detection and undetected changes of direction. Next, we use a classifier to detect when the foot touches the ground from smartphone sensor data and perform step detection. Compared with the existing SmartPDR, our proposed method improved positioning accuracy by 20% in straight walking and 70% in sideways walking.**

***Index Terms*—Indoor positioning, motion state recognition, pedestrian dead reckoning (PDR), step counting, step detection, various walking patterns.**

I. Introduction

With the widespread adoption of smartphones, users can easily confirm their current location. However, this is only possible when outdoors and GPS is available, because GPS does not work indoors or underground, it is not possible to confirm the current location [1]. Therefore, positioning methods that can be used indoors are important.

As indoor positioning methods, techniques using visible light [2], [3], acoustics [4], [5], WiFi [6], [7], bluetooth [8], and ultrawide band signals [9] have been proposed. These methods require equipment other than smartphones, potentially resulting in the need for additional dedicated equipment or installation costs. In addition, visible light and acoustic positioning may not work well in places with many tall shelves, such as supermarkets and bookstores, or when the user walks facing a wall, such as in museums and art galleries, because the signal is blocked by the shelves or the user's body [1]. Therefore, pedestrian dead reckoning (PDR) has been proposed as a positioning method that can be performed using only a smartphone and is not affected by obstacles.

PDR is a method of determining a user's relative position using sensors, such as accelerometers, gyroscopes, and magnetometers, built into smartphones. In PDR, user steps are detected, and the heading direction and step length between steps are estimated to determine the relative position with each step [10]. As mentioned, one use case of PDR is in museums and art galleries. In recent years, services that display descriptions of exhibits on smartphones are expanding. These services enable the playing of related videos on smartphones and the providing of explanations about exhibits in multiple languages [11], [12]. By tracking the visitor's location, information suitable for their situation can be provided. In addition, by observing the behavior of visitors, feedback on the layout of the exhibition space can be obtained.

When viewing exhibits in a museum, users often stand still [13]. However, if the smartphone is moving even though the user is not walking, a false step detection occurs and the location is updated wrongly [14]. In addition, we observed users' behavior in a museum and found that sideways walking may occur as the body turns toward the exhibits rather than the heading direction when walking while looking at the exhibits. This is explained in Section III-A. However, PDR assumes straight walking, so it does not function in sideways walking. For example, when transitioning from straight walking to sideways walking, the correct direction cannot be obtained because the smartphone does not rotate even if the heading direction changes [15], [16]. To solve these problems, we propose a PDR that can handle multiple walking models by classifying the user's action.

Manuscript received 9 May 2023; revised 24 July 2023 and 16 September 2023; accepted 6 October 2023. Date of publication 13 October 2023; date of current version 31 October 2023. This work was supported in part by the JST SPRING under Grant JPMJSP2119, in part by the Tateisi Science and Technology Foundation, and in part by the JSPS KAKENHI under Grant 21K17797 and Grant 22H01038. *(Corresponding author: Ibuki Yoshida.)*

This work involved human subjects or animals in its research. The authors confirm that all human/animal subject research procedures and protocols are exempt from review board approval.

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Digital Object Identifier 10.1109/JISPIN.2023.3323937

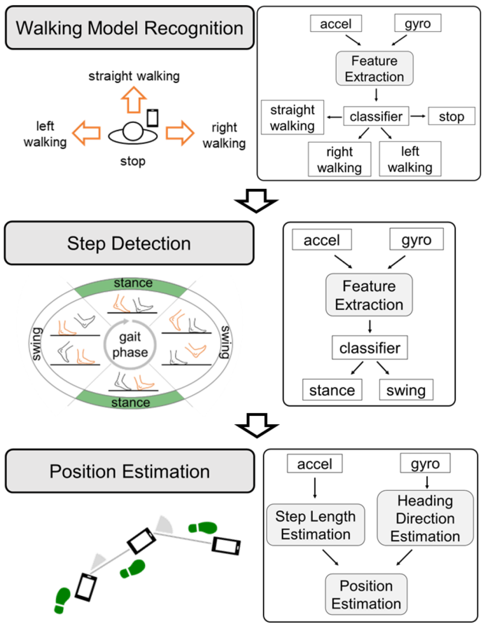

Fig. 1. Architecture of the proposed method.

Furthermore, there is an issue with PDR's step detection in sideways walking. Conventional step detection methods use peak detection based on the fact that the arm holding the smartphone moves up and down as the user's center of gravity shifts during walking [17]. However, the movement of the center of gravity is different for walking styles, so false step detection occurs in sideways walking. This problem is explained in Section IV-A. To solve this problem, we focus on the other step detection method in PDR.

As a step detection method for PDR, there is a gait phase detection method that divides the periodic movement of the feet during walking into multiple states and detects the state [18], [19]. With this method, the state of the feet is estimated by attaching sensors to the feet to detect steps. Although this method can extract only movement involved in walking, it has the disadvantage of requiring sensors to be attached to the feet. Therefore, we propose using a classifier to estimate the state of the feet only from the sensor of the smartphone.

We propose a method that classifies the user's walking model and detects the gait phase using only the smartphone sensors to achieve PDR for various walking styles. The proposed method consists of walking model recognition, step detection, and relative position estimation. An overview of the proposed method is shown in Fig. 1. The contributions of the proposed method are as follows.

1) The observation of user behaviors in museums is used to define walking models, and the proposed method classifies them. This approach can solve problems caused by irregular actions and sideways walking and support the proposed step detection method.
2) As a step detection method that can be used for both straight walking and sideways walking, we propose the gait phase detection method using only a smartphone by using a classifier.
3) Compared with the existing SmartPDR [10], the proposed method reduced the false step detection by 31% in straight walking and 59% in sideways walking and improved the positioning error by 20% in straight walking and 70% in sideways walking.

The rest of this article is organized as follows. Section II presents related work focusing on activity recognition and step detection. In Section III, we verify the walking model observed in museums and describe a walking model recognition method. Section IV proposes a step detection method using a classifier. In Section V, we explain a relative position estimation method using the results of Sections III and IV. Section VI presents performance evaluations and comparisons with existing methods. Section VII discusses future issues. Finally, Section VIII concludes this article.

II. Related Work

First, we describe the studies on PDR based on the user's activity recognition. When PDR is used with a smartphone held in the hand, the positioning results are easily influenced by the user's behavior. Therefore, studies have been done to improve positioning performance by combining PDR with the user's activity recognition. In [20], the acceleration peaks and valleys are used to detect whether the user is walking or running, and the step length is calculated using a model appropriate for the action. In [21], decision trees are used to detect how the smartphone is held, the stationary state, and irregular actions, which improve the performance of step detection. In [22], random forests (RF) and gradient boosting are used to detect how the smartphone is held, leading to improvements in both step detection and step length estimation. In [14], the support vector machine (SVM) is used to detect whether the user is walking or not, and step detection is performed only when the user is walking.

Second, we describe the studies focusing on step detection. There are two types of step detection methods: one is to detect the peak of acceleration as a step and the other is to consider walking as a periodic motion and then to detect the gait phase.

There are methods that detect steps by detecting peaks in acceleration, such as using the acceleration in the direction of gravity [10], [17] or using the acceleration norm [23], [24]. These methods utilize the fact that the position of a smartphone held in the hand changes up and down because of the movement of the center of gravity during walking [17]. However, the signal used for peak detection is affected by noise because of the body movement, resulting in false step detection. To avoid the influence of movements other than walking, methods, such as applying a low-pass filter [25] or imposing various restrictions, prevent false detection [14], [26]. Also, Abiad et al. [27] proposed a peak detection method without thresholds using machine learning. In this method, a machine learning model was created for each of acceleration and angular velocity, and the primary model was switched based on the situation to eliminate the influences of movements other than walking.

In gait phase detection, a series of walking motions are divided into several states, and steps are detected by estimating their periods. Examples of the division of the gait phase are methods

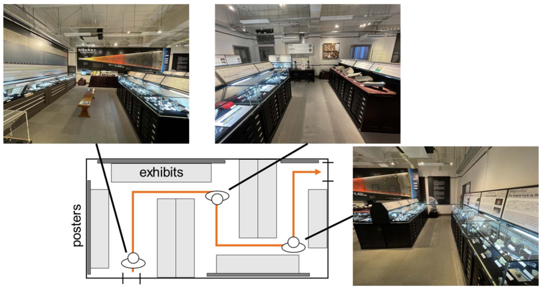

Fig. 2. Exhibition room at the Hokkaido University Museum.

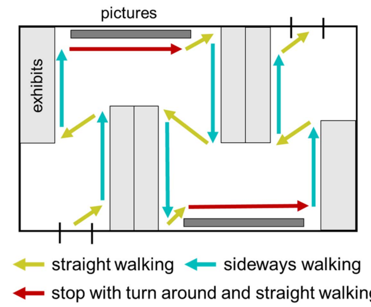

Fig. 3. Experimental environment that reproduces a museum and examples of subjects' behavior.

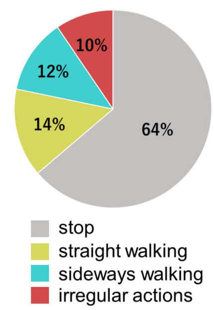

Fig. 4. Percentage of time that walking/stopping actions occurred.

that divide them into "when the foot is on the ground," "when the foot is off the ground," [18], [28], [29]. These methods attach small sensors to parts, such as the inside of shoes, shins, and heels, create features from the sensor output, and detect the gait phase based on set thresholds. Because the determination of the threshold affects the accuracy, methods have been proposed to use long short term memory (LSTM) networks to set appropriate thresholds rather than fixing them [30] or to detect states using hidden Markov models [31].

In this article, first, similar to [14] and [21], we reduce false step detection by detecting cases where the user is not walking. Second, we propose a method for detecting the gait phase using only a smartphone. The gait phase can detect steps by focusing only on foot movements, but the conventional method has limitations because sensors other than smartphones need to be attached to the feet. Our proposed method eliminates this limitation by using a classifier, allowing it to be used in a wider range of situations.

III. Walking Model Recognition

In this section, we propose a method for identifying walking models (the top of Fig. 1). First, we conduct experiments to determine what kinds of walking models occur in places, such as museums and art galleries. Second, based on the results, we define the walking models and use a classifier to identify them. In this article, we assume a situation in which descriptions of the exhibits are displayed on the smartphone. Therefore, it is assumed that the smartphone is held in the hand.

A. User Study

We reproduced an exhibition room (see Fig. 2) of the Hokkaido University Museum [32] and observed users' behaviors. There were ten subjects in total: seven in their 20 s, two in their 30 s, and one in his 50 s. The subjects were given the task of answering questions about the exhibits and were asked to walk from the entrance to the exit. Examples of subjects' behavior in an experimental environment that reproduces a museum are shown in Fig. 3. The behaviors that occurred are defined in the following four categories. The percentage of time these occurred is shown in Fig. 4.

1) *Stop:* A state of standing still to look at an exhibit.
2) *Straight walking:* Walking while facing forward.
3) *Sideways walking:* Walking while facing the exhibit.
4) *Irregular actions:* Action performed while standing still, not related to walking.

The results indicate that users are standing still for much of the time they are in museums and art galleries and that walking differently than straight walking occurs while looking at exhibits. There was no significant difference regarding age, location, and amount of time when the behavior occurred. Therefore, in this article, we conducted the experiment targeting healthy subjects in their 20 s.

Examples of irregular actions were seen in the following behaviors. Moving the arm while holding the smartphone (e.g., bringing the screen close to the face to operate a smartphone), leaning the upper body to look at the exhibits, and looking around. In particular, as shown in Fig. 3, when looking at pictures, they walked in the heading direction, stopped facing the pictures, and started walking in the heading direction again.

This experiment revealed that irregular actions and sideways walking occur. We consider that the following problems arise when using the conventional PDR in museums.

1) Because the irregular actions are caused by a smartphone moving while the user is standing still, false step detection occurs with the conventional step detection method.
2) The change in heading direction cannot be detected when transitioning from straight walking to sideways walking because the screen orientation does not change even if the heading direction changes.

To solve these problems, the proposed method detects irregular actions and eliminates them. It also detects sideways walking and corrects the heading direction.

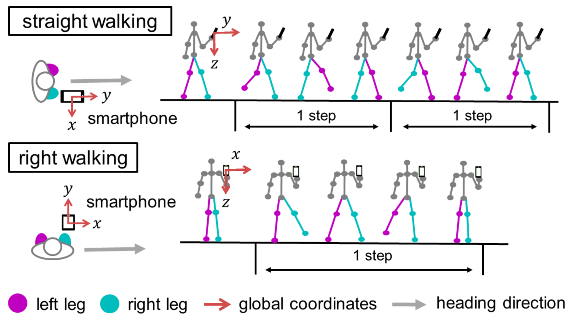

Fig. 5. Definition of the walking model and global coordinates.

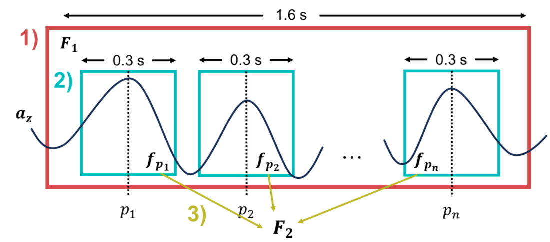

Fig. 6. Feature extraction for walking model recognition.

B. Walking Model Definition

Fig. 5 shows the definition of the walking model and global coordinates used as the sensor's coordinate system. It shows straight walking on the top and sideways walking to the right on the bottom. The global coordinates are defined as follows: the z-axis is the direction of gravity, and the y-axis is the direction of the user's body. We apply a rotation matrix with constant yaw angles to transform these global coordinates. This enables us to distinguish between straight walking and sideways walking. Straight walking moves along the y-axis because the direction of the body and the heading direction coincide. In sideways walking, they do not coincide, and the heading direction is along the x-axis. Also, to take one step, the user moves one leg in straight walking and both legs in sideways walking. Both legs do not need to touch each other every time, and this includes walking with the legs crossing each other. Sideways walking to the right from the user's perspective is defined as right walking. Left walking is defined in a similar way.

As mentioned, when irregular actions occur, a false step detection may occur and the user may be considered to have moved. However, because the user is not walking, it is desirable that no steps are detected and that the user is considered to be stationary. Therefore, in classifying the walking model, we consider the case where the user is actually standing still and the case where the user is performing irregular actions as stop.

C. Feature Extraction

To detect straight walking, right walking, left walking, and stop, we create features and use classifiers. We tried multiple window sizes, thresholds, and feature sets and selected the best ones. Then, $\boldsymbol{a_x}, \boldsymbol{a_y}, \boldsymbol{a_z}, \boldsymbol{g_x}, \boldsymbol{g_y}$, and $\boldsymbol{g_z}$ are the x-, y-, and z-axes acceleration and angular velocity data, respectively. Feature extraction is explained in Fig. 6 and as follows:

1) Calculate $\boldsymbol{F_1}$ in a window of 1.6 s. The vector $\boldsymbol{u_s}$ is obtained from the sensor data $\boldsymbol{s}$. $\boldsymbol{s}$ refers to $\boldsymbol{a_x}, \boldsymbol{a_y}, \boldsymbol{a_z}, \boldsymbol{g_x}, \boldsymbol{g_y}$, and $\boldsymbol{g_z}$ in the window. $\boldsymbol{F_1}$ is the sequence of $\boldsymbol{u_s}$. Thus, $\boldsymbol{F_1}$ has 24 elements.

$$\boldsymbol{F_1} = \begin{bmatrix} \boldsymbol{u_{a_x}} & \boldsymbol{u_{a_y}} & \boldsymbol{u_{a_z}} & \boldsymbol{u_{g_x}} & \boldsymbol{u_{g_y}} & \boldsymbol{u_{g_z}} \end{bmatrix}$$

$$\boldsymbol{u_s} = \begin{bmatrix} \min(\boldsymbol{s}) & \max(\boldsymbol{s}) & \mathrm{mean}(\boldsymbol{s}) & \mathrm{var}(\boldsymbol{s}) \end{bmatrix}.$$

2) Apply a smoothing filter every 0.15 s and detect $\boldsymbol{a_z}$ peaks with a prominence greater than 0.25.[1] The ith peak detected in the window is denoted as p_i. Calculate $\boldsymbol{f_{p_i}}$ in 0.3 s centered on p_i. The vector $\boldsymbol{v_{s_i}}$ is obtained from the sensor data $\boldsymbol{s_i}$. $\boldsymbol{s_i}$ refers to $\boldsymbol{a_{xi}}, \boldsymbol{a_{yi}}, \boldsymbol{g_{xi}}, \boldsymbol{g_{yi}}$, and $\boldsymbol{g_{zi}}$, which are $\boldsymbol{a_x}, \boldsymbol{a_y}, \boldsymbol{g_x}, \boldsymbol{g_y}$, and $\boldsymbol{g_z}$ around p_i. $\boldsymbol{f_{p_i}}$ is the sequence of $\boldsymbol{v_s}$. Thus, $\boldsymbol{f_{p_i}}$ has 10 elements

$$\boldsymbol{f_{p_i}} = \begin{bmatrix} \boldsymbol{v_{a_{xi}}} & \boldsymbol{v_{a_{yi}}} & \boldsymbol{v_{g_{xi}}} & \boldsymbol{v_{g_{yi}}} & \boldsymbol{v_{g_{zi}}} \end{bmatrix}$$

$$\boldsymbol{v_{s_i}} = \begin{bmatrix} \mathrm{mean}(\boldsymbol{s_i}) & \mathrm{var}(\boldsymbol{s_i}) \end{bmatrix}.$$

3) Calculate the mean of $\boldsymbol{f_{p_i}}$ in the window. This is denoted as $\boldsymbol{F_2}$. The number of peaks detected in the window is denoted as n. $\boldsymbol{F_2}$ is obtained as follows. Thus, $\boldsymbol{F_2}$ has 10 elements

$$\boldsymbol{F_2} = \frac{1}{n}\sum_{i=1}^{n} \boldsymbol{f_{p_i}}$$

$$= \frac{1}{n}\sum_{i=1}^{n} \begin{bmatrix} \boldsymbol{v_{a_x i}} & \boldsymbol{v_{a_y i}} & \boldsymbol{v_{g_x i}} & \boldsymbol{v_{g_y i}} & \boldsymbol{v_{g_z i}} \end{bmatrix}.$$

If no peak is detected in the window, all elements of $\boldsymbol{F_2}$ are treated as 0. The proposed method uses $\boldsymbol{F_1}$ and $\boldsymbol{F_2}$ together as features for walking model recognition, resulting in a total of 34 features.

When comparing sensor data for different walking models, notable differences were observed near the peak of $\boldsymbol{a_z}$. To capture this, we created $\boldsymbol{F_2}$, because obtaining the ideal value from all detected peaks is challenging, in 3), we calculated the average value from the data around each peak detected within the window. In the proposed method, the windows are shifted so that they overlap each other by half. The description of the classifier is given in Section VI-A.

IV. Step Detection

In this section, we discuss the problem when the conventional step detection method is applied to sideways walking. Next, we propose a step detection method (the center of Fig. 1). When users walk, the movement of the feet can be seen as periodic. Similarly, periodic signals can be observed from a smartphone held in the hand. By linking these, we propose a method for classifying foot movements and detecting steps from

[1]The implementation is based on SciPy v1.11.1.

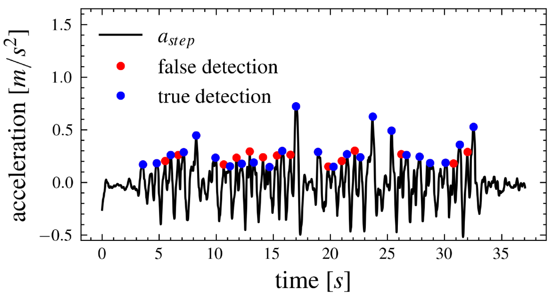

Fig. 7. Step detection of sideways walking by peak detection.

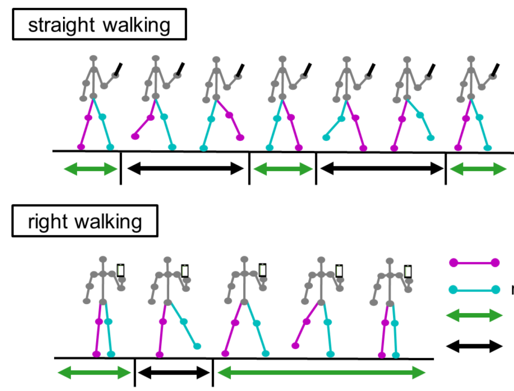

Fig. 8. Gait phase definition.

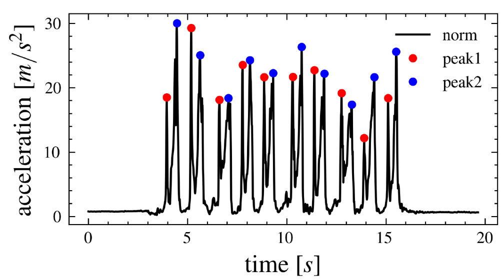

Fig. 9. Peak detection of sensors attached to the feet.

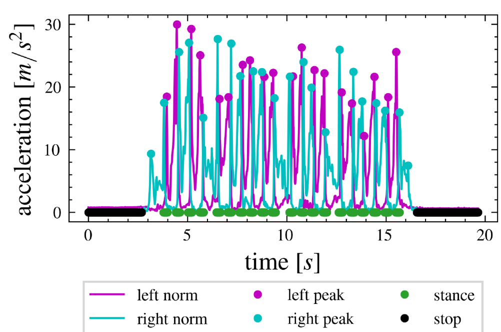

Fig. 10. Labeling results from straight walking.

the smartphone sensor output. To eliminate irregular actions, step detection is performed only when the walking model is classified as not stop.

A. Preliminary Experiment

Peak detection is one of the most commonly used step detection methods that run only on smartphones. This method detects the peak of acceleration in the direction of gravity using the fact that the center of gravity shifts while walking and uses this as a step. Here, straight walking and sideways walking are different ways of moving the legs. This indicates that in the two cases, the way the center of gravity is shifted is different.

We applied step detection with peak detection to a subject walking sideways for 10 m. The results are shown in Fig. 7. The peak was detected from $\boldsymbol{a_z}$ excluding the gravity component, $\boldsymbol{a}_{\mathbf{step}}$. The true value of steps was 24, but the detected number of steps was 37. The reasons for the false step detection are considered to be that the vertical movement of the arm holding the smartphone is smaller than during straight walking. In addition, because both legs are moved to walk one step in sideways walking, there may be two peaks for one step. This makes peak detection difficult. Therefore, we propose a step detection method that can be used even for sideways walking.

B. Training Data Preparation

We can define the gait phase as a classification class, dividing it into stance and swing. Stance refers to the state when the foot is on the ground. Swing refers to the state when the foot is off the ground. Fig. 8 shows the definition of the gait phase for straight walking on top and for sideways walking on the bottom. In straight walking, the stance is when both feet are on the ground, and in sideways walking, the stance is when the foot in the heading direction is on the ground. Any state that is not stance is defined as swing.

To label the training data, true data were obtained by walking with sensors attached to the feet. We used an IMU sensor, WT901-WiFi (see Fig. 12), that could be synchronized between multiple sensors via WiFi. We did not use a smartphone sensor, because time synchronization between multiple sensors including it was difficult. This sensor is fixed on the right foot and the left foot, and another sensor was attached to the back of a smartphone, which was held while walking.

Here, we explain the method for obtaining the true data. First, the norm of the acceleration from the sensor attached to the foot is calculated, which is shown in Fig. 9. When the norm is small, this is the stance when the foot is not moving. On the contrary, when multiple peaks can be detected, this is the swing when the foot is swinging. We detect the first peak (peak 1) seen in swing when the foot leaves the ground, and the last peak (peak 2) is detected when the foot touches the ground. Therefore, the state between peak 2 and peak 1 is defined as stance. In straight walking, because both feet are involved in moving, the common part of the stance of both feet is defined as the true stance. The result of labeling both feet in straight walking is shown in Fig. 10. In sideways walking, only the foot in the heading direction is considered to be involved in moving. Therefore, in right walking, the stance of the right foot is defined as the true stance. The same definition applies to left walking. The state that is not stance is defined as the true swing.

C. Feature Extraction

To estimate the gait phase from the sensors of a smartphone, features are calculated from the sensors attached to the back of the smartphone. The window size and the slide size are set, respectively. Features are created from the sensor data within the window, and gait phases are classified by slide size. The window size and slide size are set to 0.5–0.2 s in straight walking and 0.5–0.4 s in sideways walking, respectively. In the experiment in Section III-A, it was found that sideways walking tended to be slower than straight walking, so the slide size was set to be longer for sideways walking than for straight walking.

Different features are used for straight walking and sideways walking because the sensor output differs between the two cases. These differences are related to the user's heading direction as seen from the smartphone. Therefore, we change the acceleration used for the features of each walking model. In addition, because periodic changes in angular velocity are observed only in sideways walking, we use the angular velocity to create features. The vectors $\boldsymbol{f}_{\boldsymbol{a}_j}$ and $\boldsymbol{f}_{\boldsymbol{g}_j}$ represent the elements of the feature values obtained from the acceleration and angular velocity of the j-axis in the window. We use these vectors to represent the features $\boldsymbol{F}$ for straight walking and sideways walking

$$\text{Straight Walking}: \boldsymbol{F} = \begin{bmatrix} \boldsymbol{f}_{\boldsymbol{a}_y} & \boldsymbol{f}_{\boldsymbol{a}_z} \end{bmatrix}$$

$$\text{Sideways Walking}: \boldsymbol{F} = \begin{bmatrix} \boldsymbol{f}_{\boldsymbol{a}_x} & \boldsymbol{f}_{\boldsymbol{a}_z} & \boldsymbol{f}_{\boldsymbol{g}_x} & \boldsymbol{f}_{\boldsymbol{g}_y} & \boldsymbol{f}_{\boldsymbol{g}_z} \end{bmatrix}$$

$$\begin{aligned} \boldsymbol{f}_{\boldsymbol{a}_j} &= [\mathrm{argMax}(\boldsymbol{a}_j)\ \mathrm{argMin}(\boldsymbol{a}_j)\ \max(\boldsymbol{a}_j) - \min(\boldsymbol{a}_j) \\ &\qquad \mathrm{skewness}(\boldsymbol{a}_j)\ \mathrm{kurtosis}(\boldsymbol{a}_j)] \\ \boldsymbol{f}_{\boldsymbol{g}_j} &= [\mathrm{argMax}(\boldsymbol{g}_j)\ \mathrm{argMin}(\boldsymbol{g}_j)\ \mathrm{var}(\boldsymbol{g}_j)]. \end{aligned}$$

We use ten features for straight walking and 19 features for sideways walking. The description of the classifier is given in Section VI-A.

Peaks and valleys are detected from the gait phase classification results. The results are shown in Fig. 11. To detect peaks and valleys, $\boldsymbol{a}_{\mathbf{step}}$ obtained by subtracting the gravitational component from $\boldsymbol{a}_{\boldsymbol{z}}$ is used. As a result of step detection, the peak is the one with the maximum $\boldsymbol{a}_{\mathbf{step}}$ value among those continuously detected as stance, and the valley is the one with the minimum $\boldsymbol{a}_{\mathbf{step}}$ value between peaks. If there are candidates for peaks and valleys among those detected as stop in the walking model recognition, these are excluded.

V. Position Estimation

Using the results of the walking model recognition and step detection obtained in Sections III and IV, we estimate the heading direction, step length, and relative position (the bottom of Fig. 1). θ_k and l_k are the heading direction and stride length of the kth step, respectively. Then, the relative position of the kth step is obtained as follows:

$$\begin{cases} x_k = x_{k-1} + l_k \sin\theta_k \\ y_k = y_{k-1} + l_k \cos\theta_k. \end{cases} \tag{1}$$

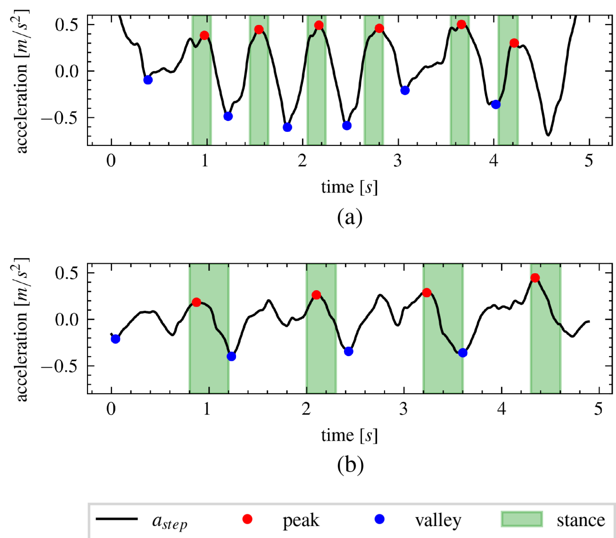

Fig. 11. Peaks and valleys obtained from gait phase detection. (a) Straight walking. (b) Sideways walking.

First, we estimate the heading direction by integrating the angular velocity. Because the values of the gyroscope include those caused by body shaking, we use the classification results of the walking model to prevent the heading direction from changing because of the body shaking in stop or irregular actions. Among the angular velocities obtained from a gyroscope, those detected as stop are set to zero. The heading direction is determined by integrating these corrected angular velocities. During walking, the heading direction is updated with each step. The user changes direction while walking only when the foot involved in the movement is off the ground. Therefore, we adopt the heading direction at the time of the valley as the heading direction for that step.

In addition, if conventional PDR is applied to cases where sideways walking occurs, there is a problem of not being able to detect the change of heading direction when the user transitions from straight walking to sideways walking. By using walking model recognition in Section III, the proposed method can detect sideways walking. Therefore, in sideways walking, the heading direction is rotated by 90° to enable position estimation even if the smartphone's orientation does not match the heading direction.

Second, the acceleration value is used to estimate the step length. We use the model equation used in SmartPDR [10]

$$l_k = \begin{cases} \beta_1 \sqrt[4]{a_{pp,k}} + \gamma_1 & a_{pp,k} < a_\tau \\ \beta_2 \log a_{pp,k} + \gamma_2 & a_{pp,k} \geq a_\tau \end{cases} \tag{2}$$

$$a_{pp,k} = a_{\mathrm{peak},k} - a_{\mathrm{valley},k} \tag{3}$$

where $a_{\mathrm{peak},k}$ and $a_{\mathrm{valley},k}$ is the value of $\boldsymbol{a}_{\mathbf{step}}$ at the peak, valley of the kth step. The a_τ, β_1, γ_1, β_2, and γ_2 are hyperparameters set for straight walking and sideways walking, respectively. The parameters used are listed in Table I.

TABLE I
HYPERPARAMETERS USED IN STEP LENGTH ESTIMATION

parameter	straight	sideways
a_T	0.6	0.6
β_1	0.25	0.20
γ_1	0.35	0.45
β_2	0.20	0.15
γ_2	0.45	0.55

Fig. 12. WT901-WIFI.

VI. EXPERIMENTS AND EVALUATION

To verify the performance of the proposed method, three experiments were conducted. The first experiment was conducted to obtain training data. Leave-one-person-out cross validation was performed on the data obtained from this experiment to evaluate the walking model recognition performance, step detection performance, and position estimation performance. The second experiment involved using multiple smartphones to verify whether the proposed method is independent of the type of smartphone. Finally, an experiment was conducted in an environment simulating a museum to verify the position estimation performance.

The walking data of eight subjects were collected. One subject's data were selected as test data, and the remaining seven subjects' data as training data. When verifying the performance, the data of the target subjects were not included in the training data. For supervised learning classifiers, RF, SVM, and logistic regression (LR) were used[2] to compare classification performance. The true values of the experiments were set as follows. The number of steps was counted visually by the author. For positioning, we used MotionAnalysis's Mac3D System, which is an optical motion capture system with a positioning error of less than a few millimeters. The sampling frequency is 100 Hz for all sensors.

A. Training Data and Cross Validation

We conducted an experiment to obtain training data. We used WT901-WiFi from WitMotion (shown in Fig. 12) as the sensor to calculate features for walking model recognition and step detection. We used the Google Pixel 2 XL as the smartphone to estimate position. During the experiment, we attached the sensor to the back of the smartphone held in the hand and fixed the sensor to the foot so that it would not move while walking (see Fig. 13). The sensor attached to the foot was used to obtain the true data for the gait phase classification and was not used for positioning.

[2]The implementation is based on scikit-learn 1.2.2.

Fig. 13. Sensor fixed to the foot.

Fig. 14. Walking model recognition performance.

We obtained data for eight subjects with different genders, ages, and heights. The subjects consisted of six males and two females, aged between 21 and 25, and with heights ranging from 156 to 178 cm. In the experiment conducted in Section III-A, we targeted healthy subjects, and we observed no age-specific differences in the walking model. Therefore, we recruited young people as subjects. We used data from three rounds of walking a rectangular path of 2 m $\times$ 3 m for straight walking, right walking, and left walking, totaling 30 m. In sideways walking, we instructed the subjects as follows. Assume a situation in which they are walking while looking at exhibits in a museum, and keep the body facing the direction of exhibits. Examples of the walking style are shown in Figs. 5 and 8. As irregular actions, the subjects moved the smartphone up and down 20 times and forward and backward 20 times while standing still. From the examples of irregular actions obtained in the experiments in Section III-A, we selected the motion of moving the arm while holding the smartphone because these behaviors showed peaks that would cause false step detection. Although we also observed other actions, such as looking around while standing still and leaning the upper body to look at an exhibition, these actions did not produce such peaks. Therefore, we did not include these behaviors in this experiment because they are considered to have no effect on step detection with the existing methods.

We created training data from this experiment and used it for our proposed method. We conducted leave-one-person-out cross validation to verify the performance of our proposed method.

1) Walking Model Recognition Performance: We verified the classification performance of walking models and the results are shown in Fig. 14. We trained classifiers using data obtained from the experiment, with 2513 samples. As supervised classifiers, RF, SVM, and LR were used, with RF having the best

TABLE II
GAIT PHASE CLASSIFIER PERFORMANCE

walking model	accuracy	precision	recall	f1-score
straight walking	0.90	0.90	0.89	0.90
right walking	0.85	0.88	0.83	0.85
left walking	0.83	0.85	0.84	0.83

performance with 88% accuracy. Regarding the parameters of the RF used, the number of trees was 13 and the depth of trees was 4. Fig. 14 shows that the system can detect the stop condition, including irregular actions. This allows the proposed method to remove motions unrelated to walking from the positioning.

Although not observed in the experiment in Section III-A, it is expected that users will rotate their smartphones from vertical to horizontal because some services display videos about the exhibits on their smartphones. Because the proposed method uses a global coordinate system and the motion of rotating the smartphone can be regarded as irregular action, we consider that positioning is not affected in such cases.

2) Step Detection Performance: First, we verified the classification performance of gait phases for each walking model. The training data for straight walking, right walking, and left walking were 4292, 4125, and 4051 samples, respectively. As supervised classifiers, RF, SVM, and LR were used, with RF having the best performance for all walking models. Therefore, RF is used in the proposed method. Regarding the parameters of the RF used, the number of trees is 13 and the depth of trees is 4. The results are given in Table II.

From Table II, we considered that gait phases could be detected using the classifiers. The accuracy is still low for sideways walking and is not as good as that in straight walking. This is considered to be because of the individual differences in upper body movements during walking. However, in the use of positioning, it is sufficient to detect the number of steps accurately rather than obtain gait phases accurately at intervals, such as slide size.

Next, we verified the performance of step detection for each walking model. As a result, Table III gives the step detection rate (SDR), which represents the ratio of the number of detected steps to the true number of steps, mean absolute error (MAE), and maximum error (MAX) for each walking model. As a reference, the mean number of steps was 61.5 steps in straight walking, 63.0 steps in right walking, and 62.6 steps in left walking. Using the training data created with WitMotion, we calculated the number of steps from the smartphone data. As a comparative method, we used the peak detection method of SmartPDR applied to the smartphone data. In this method, peak detection is performed by setting various parameters. We adjusted the parameters to minimize the absolute error for each subject and used it as a comparative method. The parameters we adjusted are the threshold of the peak to be detected, the threshold of the difference between the current peak and the valleys before and after it, and the number of samples to be used when comparing with the threshold.

From Table III, we compared the step detection performance between the proposed method and SmartPDR. The proposed

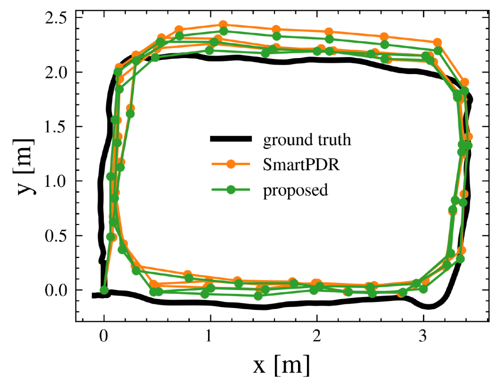

Fig. 15. Positioning result for straight walking.

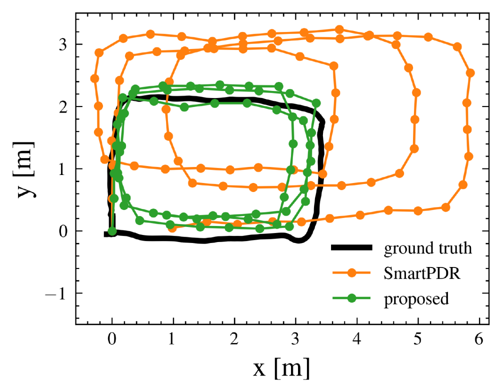

Fig. 16. Positioning result for right walking.

method can reduce the false step detection by 31% in straight walking and by 59% in sideways walking. Many conventional peak detection methods, such as SmartPDR, apply various constraints to prevent false step detection, but these require more parameter settings suitable for each individual. Therefore, the proposed method has an advantage in saving the effort of setting these parameters.

3) Position Estimation Performance: We verified the performance of using smartphone data for positioning. As a comparison method, we used SmartPDR. This method uses a magnetometer to estimate the heading direction, but it does not work properly because the experimental environment was a building surrounded by reinforced concrete. Therefore, we excluded the direction obtained from the magnetometer when comparing the two methods. The parameters related to step detection in SmartPDR were set for each participant and used as a comparison method for positioning. We plotted the first lap as the ground truth and show the best positioning results using the proposed method and SmartPDR for straight walking, right walking, and left walking in Figs. 15–17, respectively. We present the positioning errors obtained from the positioning results in Table IV.

From Table IV, the proposed method can improve the positioning error by 20% in straight walking and by 70% in sideways walking. The accuracy was comparable for straight walking, but the proposed method greatly improved the accuracy for sideways walking. The reason for the decreased performance of SmartPDR in sideways walking is that the appropriate step is

TABLE III
STEP DETECTION PERFORMANCE SHOWN USING SDR, MAE, AND MAX

	proposed			SmartPDR		
walking model	SDR (%)	MAE (steps)	MAX (steps)	SDR (%)	MAE (steps)	MAX (steps)
straight walking	98.2	1.13	4	97.3	1.63	4
right walking	95.6	2.75	5	91.3	5.50	10
left walking	95.4	2.88	4	92.0	5.00	10

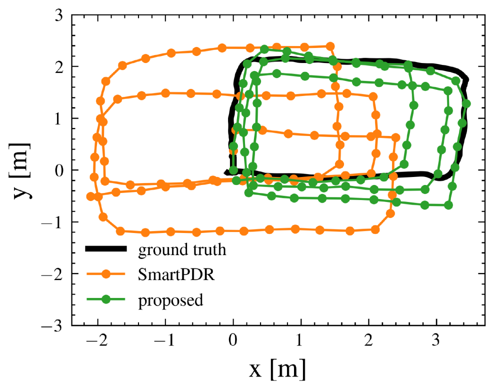

Fig. 17. Positioning result for left walking.

TABLE IV
POSITIONING PERFORMANCE

	proposed		SmartPDR	
walking model	MAE (m)	SD (m)	MAE (m)	SD (m)
straight walking	0.54	0.21	0.68	0.17
right walking	0.52	0.25	2.15	0.89
left walking	0.52	0.23	1.45	0.62

not detected because the leg movement is different from that of straight walking.

B. Performance of Smartphone Models

To demonstrate that the proposed method is independent of smartphone models, experiments were conducted using multiple smartphones. Three types of smartphones, Galaxy S10+, Google Pixel 2 XL, and Sony XQ-BE42, were used in the experiment. The data were obtained by walking the same route as in the experiment in Section VI-A3. The experiment was conducted five times for each model and walking method. As a comparative method, SmartPDR, which adjusts parameters for each data, was used similarly to Section VI-A3. Table V gives the positioning errors calculated based on the positioning results.

Table V gives that regardless of the smartphone model used, the accuracy in straight walking was equivalent to that of SmartPDR, and in sideways walking, the proposed method significantly improved the accuracy.

C. Performance for Use in a Museum

We conducted an experiment assuming the environment of a museum. A subject walked a rectangular path of 10 m, 2 long, and 3 m wide, 10 times, as if walking while viewing exhibits in a museum, and used it for verification. The smartphone used in the experiment was a Google Pixel 2 XL. Fig. 18 shows the transition of walking during the experiment. First, the subject walked

TABLE V
POSITIONING PERFORMANCE FOR MULTIPLE SMARTPHONES

(a) Straight walking.

	proposed		SmartPDR	
smartphone	MAE (m)	SD (m)	MAE (m)	SD (m)
Galaxy S10+	0.58	0.31	0.66	0.30
Google Pixel 2 XL	0.46	0.24	0.60	0.31
Sony XQ-BE42	0.57	0.30	0.71	0.38

(b) Right walking.

	proposed		SmartPDR	
smartphone	MAE (m)	SD (m)	MAE (m)	SD (m)
Galaxy S10+	0.63	0.28	2.61	0.65
Google Pixel 2 XL	0.60	0.22	2.68	0.87
Sony XQ-BE42	0.67	0.29	2.51	1.18

(c) Left walking.

	proposed		SmartPDR	
smartphone	MAE (m)	SD (m)	MAE (m)	SD (m)
Galaxy S10+	0.70	0.21	2.85	0.30
Google Pixel 2 XL	0.57	0.30	2.82	0.31
Sony XQ-BE42	0.61	0.19	2.34	1.38

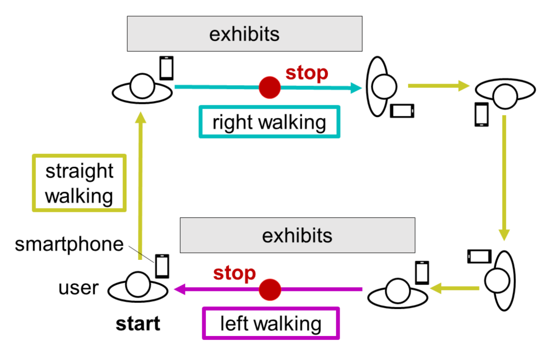

Fig. 18. Experiment for use in a museum.

straight toward the exhibit and then walked sideways to the right while viewing the exhibit. Next, the subject walked straight ahead and headed toward the next exhibit. Finally, the subject walked sideways to the left while viewing the exhibit. Also, a three-s stop was implemented during the sideways walking while viewing the exhibit. It should be noted that when changing from straight walking to right walking at the first turn, the direction of progress changes, but the direction of the smartphone does not change. In conventional methods, there is a problem in that such a change in direction cannot be detected.

Fig. 19 shows the positioning results of the proposed method and SmartPDR. In the positioning results of the proposed method, the detected models are also plotted. The mean error and standard deviation of the proposed method were 0.42 m and 0.24 m, respectively, while those of SmartPDR were 8.09 m and 0.79 m. Based on these results, our proposed method can

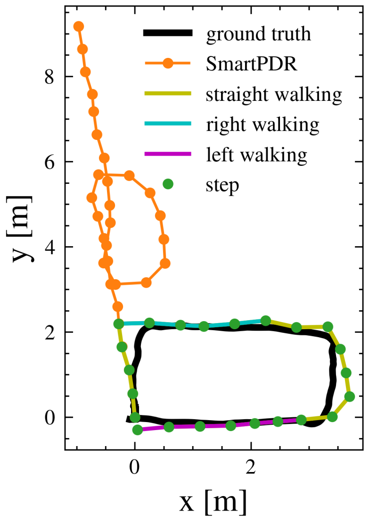

Fig. 19. Positioning results for use in a museum.

perform positioning even in cases with multiple walking models. SmartPDR fails to detect the change from straight walking to right walking at the first turn and continues walking in the same direction. Even at the last turn, where the heading direction is changed from straight walking to left walking, the positioning result is moving in the wrong direction because it considers the change of body direction as a change of heading direction even though the heading direction is not changed. This result shows the importance of model detection.

VII. Discussion

We proposed to detect the user's walking style and to perform positioning by step detection using a classifier. This improves the problem of false step detection because of irregular actions and the problem of not detecting correct changes of direction or steps because of sideways walking. However, the proposed method has the following two problems.

1) This method only works when holding a smartphone.
2) The number of walking models assumed is limited.

First, at present, the proposed method assumes that the smartphone is only held in the hand. However, it is considered that if we increase the training data, the system can be used when a smartphone is in a pocket or a bag. This expands the environment in which the system can be used.

Second, we defined and experimented with models for straight walking and sideways walking in this article. However, in reality, walking styles differ depending on their situations. It is considered that there are many different walking models, such as a combination of straight and sideways walking. Classifying these styles and determining the appropriate positioning method are tasks for future research.

VIII. Conclusion

In this article, we propose a novel step detection method that can be used in situations, such as walking, while looking at exhibits in a museum even if the user performs irregular actions or walks sideways. We show that the proposed method improves positioning performance. The proposed method removes false step detection by recognizing stop and irregular actions. Moreover, by detecting sideways walking, the method can estimate the correct direction even when the heading direction and the direction of the smartphone do not coincide. Furthermore, by using a classifier, we propose a step detection method that detects the gait phase using only a smartphone. This method can be used for both straight walking and sideways walking, eliminating the limitation of the conventional method that requires a sensor attached to the foot. As an evaluation experiment, we compared the proposed method with the existing SmartPDR. As a result, the false detection rate of steps was reduced by 31% in straight walking and 59% in sideways walking, and the positioning error improved by 20% in straight walking and 70% in sideways walking.

References

[1] Q. Wang et al., "Recent advances in pedestrian inertial navigation based on smartphone: A review," *IEEE Sensors J.*, vol. 22, no. 23, pp. 22319–22343, Oct. 2022.

[2] R. Huitl, G. Schroth, S. Hilsenbeck, F. Schweiger, and E. Steinbach, "TUMindoor: An extensive image and point cloud dataset for visual indoor localization and mapping," in *Proc. IEEE 19th Int. Conf. Image Process.*, 2012, pp. 1773–1776.

[3] S. Shimada, H. Hashizume, and M. Sugimoto, "Indoor positioning using reflected light and a video camera," in *Proc. Int. Conf. Indoor Positioning Indoor Navigat.*, 2018, pp. 1–8.

[4] C. Peng, G. Shen, Y. Zhang, Y. Li, and K. Tan, "Beepbeep: A high accuracy acoustic ranging system using cots mobile devices," in *Proc. 5th Int. Conf. Embedded Networked Sensor Syst.*, 2007, pp. 1–14.

[5] M. Nakamura, K. Fujimoto, H. Murakami, H. Hashizume, and M. Sugimoto, "Indoor localization method for a microphone using a single speaker," in *Proc. Int. Conf. Indoor Positioning Indoor Navigat.*, 2021, pp. 1–8.

[6] P. Bahl and V. N. Padmanabhan, "RADAR: An in-building RF-based user location and tracking system," in *Proc. IEEE INFOCOM Conf. Comput. Commun. 19th Annu. Joint Conf. IEEE Comput. Commun. Societies*, 2000, pp. 775–784.

[7] M. T. Hoang, B. Yuen, X. Dong, T. Lu, R. Westendorp, and K. Reddy, "Recurrent neural networks for accurate RSSI indoor localization," *IEEE Internet Things J.*, vol. 6, no. 6, pp. 10639–10651, Sep. 2019.

[8] R. Faragher and R. Harle, "Location fingerprinting with bluetooth low energy beacons," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 11, pp. 2418–2428, Nov. 2015.

[9] S. Krishnan, P. Sharma, Z. Guoping, and O. H. Woon, "A UWB based localization system for indoor robot navigation," in *Proc. IEEE Int. Conf. Ultra-Wideband*, 2007, vol. 20, no. 17, pp. 10283–10294.

[10] W. Kang and Y. Han, "SmartPDR: Smartphone-based pedestrian dead reckoning for indoor localization," *IEEE Sensors J.*, vol. 15, no. 5, pp. 2906–2916, Dec. 2014.

[11] "Tokyo national museum art guide," Accessed:Jul. 1 2023. [Online]. Available: https://www.tnm.jp/modules/r_free_page/index.php?id=2010&lang=en

[12] "Detroit Institute of Arts, Lumin," Accessed: Jul. 1 2023 [Online]. Available: https://dia.org/about/media-room/news/detroit-institute-arts-wins-2017-muse-gold-award-its-augmented-reality-tour

[13] F. Hachem, D. Vecchia, M. L. Damiani, and G. P. Picco, "Fine-grained stop-move detection in UWB-based trajectories," in *Proc. IEEE Int. Conf. Pervasive Comput. Commun.*, 2022, pp. 111–118.

[14] X. Wang, G. Chen, X. Cao, Z. Zhang, M. Yang, and S. Jin, "Robust and accurate step counting based on motion mode recognition for pedestrian indoor positioning using a smartphone," *IEEE Sensors J.*, vol. 22, no. 6, pp. 4893–4907, Feb. 2021.

[15] S. Shimizu, N. Ito, K. Naito, N. Chujo, T. Mizuno, and K. Kaji, "Pedestrian direction estimation for each step using plane component of accelerometer," in *Proc. 10th Int. Conf. Mobile Comput. Ubiquitous Netw.*, 2017, pp. 1–6.

[16] S. Park, J. H. Lee, and C. G. Park, "Robust pedestrian dead reckoning for multiple poses in smartphones," *IEEE Access*, vol. 9, pp. 54498–54508, 2021.

[17] J. W. Kim, H. J. Jang, D.-H. Hwang, and C. Park, "A step, stride and heading determination for the pedestrian navigation system," *J. Glob. Positioning Syst.*, vol. 3, no. 1-2, pp. 273–279, Feb. 2004.

[18] E. Foxlin, "Pedestrian tracking with shoe-mounted inertial sensors," *IEEE Comput. Graph. Appl.*, vol. 25, no. 6, pp. 38–46, Nov. 2005.

[19] X. Tao, F. Zhu, X. Hu, W. Liu, and X. Zhang, "An enhanced foot-mounted PDR method with adaptive ZUPT and multi-sensors fusion for seamless pedestrian navigation," *GPS Solutions*, vol. 26, Nov. 2021, Art. no. 13.

[20] X. Li, J. Wang, and C. Liu, "A Bluetooth/PDR integration algorithm for an indoor positioning system," *Sensors*, vol. 15, no. 10, pp. 24862–24885, Sep. 2015.

[21] M. Susi, V. Renaudin, and G. Lachapelle, "Motion mode recognition and step detection algorithms for mobile phone users," *Sensors*, vol. 13, no. 2, pp. 1539–1562, Jan. 2013.

[22] I. Klein, Y. Solaz, and G. Ohayon, "Pedestrian dead reckoning with smartphone mode recognition," *IEEE Sensors J.*, vol. 18, no. 18, pp. 7577–7584, Jul. 2018.

[23] L. Ojeda and J. Borenstein, "Non-GPS navigation for security personnel and first responders," *J. Navigation*, vol. 60, no. 3, pp. 391–407, Feb. 2007.

[24] H. Zhang, W. Yuan, Q. Shen, T. Li, and H. Chang, "A handheld inertial pedestrian navigation system with accurate step modes and device poses recognition," *IEEE Sensors J.*, vol. 15, no. 3, pp. 1421–1429, Oct. 2014.

[25] B. Wang, X. Liu, B. Yu, R. Jia, and X. Gan, "Pedestrian dead reckoning based on motion mode recognition using a smartphone," *Sensors*, vol. 18, no. 6, Jun. 2018, Art. no. 1811.

[26] S. Lee, B. Kim, H. Kim, R. Ha, and H. Cha, "Inertial sensor-based indoor pedestrian localization with minimum 802.15. 4a configuration," *IEEE Trans. Ind. Informat.*, vol. 7, no. 3, pp. 455–466, Aug. 2011.

[27] N. Al Abiad, Y. Kone, V. Renaudin, and T. Robert, "Smartstep: A robust step detection method based on smartphone inertial signals driven by gait learning," *IEEE Sensors J.*, vol. 22, no. 12, pp. 12288–12297, Jun. 2022.

[28] A. R. Jiménez, F. Seco, J. C. Prieto, and J. Guevara, "Indoor pedestrian navigation using an INS/EKF framework for yaw drift reduction and a foot-mounted IMU," in *Proc. 7th Workshop Positioning Navigation Commun.*, 2010, pp. 135–143.

[29] I. Skog, J.-O. Nilsson, and P. Händel, "Evaluation of zero-velocity detectors for foot-mounted inertial navigation systems," in *Proc. Int. Conf. Indoor Positioning Indoor Navigation*, 2010, pp. 1–6.

[30] M. Edel and E. Köppe, "An advanced method for pedestrian dead reckoning using BLSTM-RNNs," in *Proc. Int. Conf. Indoor Positioning Indoor Navigation*, 2015, pp. 1–6.

[31] F. Della Rosa, M. Pelosi, and J. Nurmi, "Human-induced effects on RSS ranging measurements for cooperative positioning," *Int. J. Navigation Observation*, vol. 2012, Sep. 2012, Art. no. 13.

[32] "The Hokkaido University Museum," Accessed: Apr. 25, 2023. [Online]. Available: https://www.museum.hokudai.ac.jp/