Intelligent Fusion of Wi-Fi and Inertial Sensor-Based Positioning Systems for Indoor Pedestrian Navigation

Lyu-Han Chen, Eric Hsiao-Kuang Wu, Ming-Hui Jin, and Gen-Huey Chen

***Abstract*— Indoor positioning systems based on wireless local area networks are growing rapidly in importance and gaining commercial interest. Pedestrian dead reckoning (PDR) systems, which rely on inertial sensors, such as accelerometers, gyroscopes, or even magnetometers to estimate users' movement, have also been widely adopted for real-time indoor pedestrian location tracking. Since both kinds of systems have their own advantages and disadvantages, a maximum likelihood-based fusion algorithm that integrates a typical Wi-Fi indoor positioning system with a PDR system is proposed in this paper. The strength of the PDR system should eliminate the weakness of the Wi-Fi positioning system and *vice versa*. The intelligent fusion algorithm can retrieve the initial user location and moving direction information without requiring any user intervention. Experimental results show that the proposed positioning system has better positioning accuracy than the PDR system or Wi-Fi positioning system alone.**

***Index Terms*— Dead reckoning, indoor positioning, received signal strength, sensor, WLAN.**

I. Introduction

WITH the advent of wireless technologies and the proliferation of mobile computing devices, diverse requirements (e.g., context awareness, visitor guidance, health care, and personalized information delivery) have rapidly fostered the development of positioning and navigation services, which can offer the changing information of individual customers' locations. The global positioning system (GPS) [1] is a well-known system and is widely used for outdoor positioning. However, it is not suitable for indoor environments because it requires an unblocked transmission path to receive GPS signals.

A great number of solutions to the indoor positioning problem have been suggested in related industry literature [2]–[21]. The solutions proposed in [2] and [3] are based on cellular signals, which suffer from poor accuracy and bad vertical floor resolution in indoor environments [4]. More and more solutions [5]–[14] utilize IEEE 802.11 wireless local area networks (WLANs) (i.e., Wi-Fi) to provide efficient indoor positioning services, due to their wide availability and ubiquitous coverage in indoor environments. Among them, the received signal strength (RSS)-based approaches [7]–[14] are more feasible in practice because RSSs from access points (APs) can be measured easily by simple and cheap mobile devices. For example, the fingerprint scheme is a popular RSS-based Wi-Fi positioning scheme in indoor environments. However, the severe fluctuation of RSSs in indoor environments causes inaccurate positioning results.

On the other hand, over the last decade, some methods based on inertial measurement units (IMUs) have been proposed for indoor positioning or tracking [15]–[21]. These methods, often called pedestrian dead reckoning (PDR) solutions, all rely on inertial sensors such as accelerometers, gyroscopes, or even magnetometers to estimate relative displacement, starting with the known initial user location. At each detected step of a user, the location update is accomplished by adding the current estimated displacement to the previously estimated location. Recently, since more and more hand-held devices are equipped with inertial sensors, PDR solutions are more and more practicable in our daily lives. Furthermore, PDR solutions require no additional infrastructure. However, since the estimation is based on noisy inertial sensors, the tracking error of a PDR system can accumulate over time. Additionally, the initial user location is not necessarily available when the tracking service is requested by a user, which makes tracking difficult and inaccurate.

Since RSS-based Wi-Fi positioning approaches apply location-dependent RSSs for indoor positioning, the positioning results can be used to bind the cumulative PDR tracking error. On the other hand, PDR systems can provide continuous tracking, and thus, they can overcome the fluctuation of RSS-based Wi-Fi positioning due to the fluctuation of RSSs. Therefore, a more effective way to enhance the accuracy of indoor positioning is to fuse an RSS-based Wi-Fi positioning system with a PDR system. Both the PDR system and the Wi-Fi positioning system are expected to be complementary to each other.

Recently, some approaches [15]–[18] that can provide RSS-based Wi-Fi positioning systems with PDR solutions have been proposed. In [15] and [16], two fingerprint-based methods are presented to estimate the user's location by the aid of a particle filter [22], which is based on Monte-Carlo sampling and thus can deal with non-linear and non-Gaussian estimation problems. When the current step of the user is detected by the inertial sensors in the PDR system, the stride

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length that is estimated is fed into the particle filter as a movement model to sample the new positions of particles. The particles have different moving directions, and their moving distances are normally distributed with a mean equal to the measured stride length.

In [15], the weight of a particle in the uth step is set to:

$$w^u = \frac{1}{\sqrt{2\pi\sigma^2}} \times \exp\{\frac{-|X^u - Y^u|^2}{2\sigma^2}\},$$

where $u \geq 1$, X^u denotes the location of the particle, Y^u denotes the location of the user that is estimated by the fingerprint method, $|X^u - Y^u|$ means the distance between X^u and Y^u, and σ is the variance of RSSs. In [16], the particle weight in the uth step is set to $w^u w^{u-1}$, where $w^0 = 1/N$ and N is the number of particles. The user's location is estimated according to all particle weights. Also, the performance of the particle filter can be further improved, if the map of a building is available. We only set $w^u = 0$, whenever the particle hits a wall. However, the positioning may be not accurate if the location (i.e., Y^u) estimated by the fingerprint method is not stable. Furthermore, if using a PDR system, the initial user location must be provided.

In [17], Wi-Fi signal strengths, inertial sensors, a detailed building map, and a particle filter are used to track a user without requiring the initial user location information in advance. Multiple floors and stairways can be handled as well. The Wi-Fi signal strengths are used to constrain the initial user location, so particles can be scattered in a restricted region, instead of being scattered over the whole building. The particles move in the same way, as in [15] and [16], and one is eliminated whenever it hits a wall. The positioning is accomplished mainly by comparing the trajectory (obtained from the PDR system) of the user with the building map. As a consequence, the positioning accuracy depends highly on the moving behavior of the user. When the moving behavior is simple (e.g., walking along a corridor), the positioning error may be large.

In [18], when using a smartphone for positioning, a set of techniques, such as step counting and heading estimation, are provided to the PDR system, so that it does not assume knowledge of the placement of a user's smartphone i.e., whether it is in the user's hand, shirt pocket, bag, or elsewhere). Furthermore, the smartphone enables zero-effort crowdsourcing of Wi-Fi signal strengths in indoor spaces for the Wi-Fi positioning system by the aid of inertial sensors. However, the Wi-Fi signal strengths are used to constrain the initial user location. The key idea of positioning in [18] is to compare the trajectory (obtained from the PDR system) of the user with the building map. Therefore, positioning accuracy also highly depends on the moving behavior of the user.

Besides, there are some approaches in [19] and [20] that integrate PDR systems with RSSs obtained from RFID tags [19] or IEEE 802.15.4a radio beacons [20]. In [19], although the cumulative PDR tracking error is limited, the RFID tags must be sufficient and well deployed (e.g., deployed along or near the trajectory of the user) so as to render an accurate positioning. In [20], although the positioning is accurate for a spacious area, it gets worse, as a consequence of a serious RSS fluctuation, if there are corridors. Therefore, the fusion approaches used in [19] and [20] are not suitable for integrating a Wi-Fi positioning system with a PDR system.

The approach in [21] tracks the user by the aid of the PDR system. Besides, it observes that some locations, called landmarks, in an indoor environment present identifiable signatures on one or more sensing dimensions. For example, an elevator imposes a distinct pattern on a smartphone's accelerometer and a unique set of Wi-Fi APs can be detected in some corners. Hence, it considers that as long as the positions of the landmarks are known, the positioning error can be reduced when the user passes through any of the landmarks, although the tracking error of the PDR system can accumulate over time. However, there is no guarantee that sufficient landmarks can be found in the indoor environment, and the positions of the landmarks are difficult to estimate precisely. Further, if the range of the landmark is large, the positioning error is still large.

In this paper, an intelligent indoor positioning algorithm that fuses a PDR system and an RSS-based Wi-Fi positioning system is proposed without requiring the initial user location and initial user moving direction information in advance. Specifically, the word 'intelligent' indicates that the initial user location and moving direction data can be derived by the proposed methods automatically without requiring any user input or user intervention.

The algorithm consists of two phases. In the first phase, the initial user location and moving direction are determined sequentially. The former is determined by using relative displacements of the user in different time periods, which can be obtained from the PDR system, and the locations estimated by the Wi-Fi positioning system. The latter is determined by the aid of regression analysis, which can be used to model the distribution of the locations estimated by the Wi-Fi positioning system.

In the second phase, since it is rather time-consuming to use a particle filter [22], we propose a maximum likelihood (ML)-based fusion algorithm that consumes less time and induces a more accurate positioning compared to the algorithms in [15]–[18]. In the proposed fusion algorithm, a tradeoff between the locations estimated by the Wi-Fi and the PDR positioning systems is considered. The fusion algorithm takes into account some of the latest locations that are estimated by the Wi-Fi and the PDR positioning systems for the purpose of stable positioning. To demonstrate the effectiveness of the proposed positioning algorithm, experiments were carried out in the Nangang exhibition hall of Taipei City. Experimental results show that the proposed algorithm has significant improvements in positioning accuracy.

The rest of this paper is organized as follows. In Section II, we describe an RSS-based Wi-Fi positioning system used in this experiment and the issues of the inertial sensors that we employ in our proposed system. In Section III, an indoor positioning algorithm that fuses the PDR system and the RSS-based Wi-Fi positioning system is proposed. In Section IV, the effectiveness of the indoor positioning algorithm is demonstrated by experiments. Finally, Section V concludes with some remarks.

II. Preliminary

In this section, a proposed RSS-based Wi-Fi positioning system is first presented. The issues of inertial sensors that we employ are then presented.

A. RSS-Based Wi-Fi Positioning System

Currently, the most viable solution for RSS-based Wi-Fi positioning is the fingerprint scheme. Further, in the fingerprint scheme, it was indicated in [8] that probabilistic approaches such as the ML estimator [9] are more accurate in positioning than deterministic approaches. Therefore, the ML estimator is adopted to be the core of the RSS-based Wi-Fi positioning system used in this paper. The fingerprint scheme and the ML estimator are briefly described below.

The fingerprint scheme works in two stages: offline and online. During the offline stage, RSSs from all APs are collected at each sampling location, named the reference point (RP), to build a database, named the radio map. During the online stage, a user measures RSSs from all APs, and the user's location is estimated by examining the difference between the measured RSSs and the RSSs stored in the radio map.

Assume that there are m APs, denoted by AP_1, AP_2,..., AP_m, and n RPs, denoted by RP_1, RP_2, ..., RP_n. A matrix $\Re=[\delta_{i,j}]$ is used to represent the radio map, where $1\leq i\leq m$, $1\leq j\leq n$, and $\delta_{i,j}$ is the probability density function of RSSs from AP_i collected at RP_j during a fixed time period. The RSSs measured by the user are conveniently represented by a vector $S=[s_1, s_2, \ldots, s_m]$, where s_i is the average of the RSSs from AP_i measured during a short time period.

In the ML estimator, the positioning problem can be regarded as finding the highest $P(w_r|S)$, where w_r represents the coordinate of the r-th RP. By using the Bayes' rule, the probability can be calculated as:

$$P(w_r|S) = \frac{P(S|w_r)P(w_r)}{P(S)} = C \times P(S|w_r),$$

where C is a constant. In this case, the probability $P(w_r|S)$ depends only on the likelihood $P(S|w_r)$, and $P(S|w_r)$ can be calculated as:

$$P(S|w_r) = \prod_{i=1}^{m} \delta_{i,r}(s_i).$$

The location estimation rule is

$$\hat{w} = \underset{1\leq r\leq n}{\arg\max}\ P(S|\,w_r),$$

where $\hat{w}$ is the estimated coordinate of the user.

B. Inertial Sensors

An off-the-shelf smartphone is usually equipped with an IMU, which has several sensors such as accelerometers and magnetometers. In this paper, we use a commercially available IMU for tracking the user. Theoretically, the moving distance of the user can be obtained by using the acceleration data provided by an IMU. However, the acceleration for an indoor pedestrian is small, and can be easily affected by sensor noises. An alternative approach is to detect the walking step. Hence, the moving distance, denoted by D, can be estimated as

$$D = num\_steps \times step\_length,$$

where *num_steps* represents the number of walking steps and *step_length* represents the length of each walking step.

Since the vertical acceleration fluctuates periodically due to human motion, a peak detection algorithm is used to estimate the value of *num_steps* (i.e., one peak of acceleration stands for one walking step). Also notice that the peak can be affected by the user's walking practice. Suppose that T_{min} is the minimum time interval between two continuous peaks. If more than two peaks are measured during T_{min}, only the first peak is counted as a step to prevent an overestimate. We set $T_{min} = 0.3$ (sec.) as in [20]. The value of *step_length* can be easily estimated by counting the number of walking steps required for the user to traverse a specified distance. The moving direction or heading information can be obtained by the aid of the magnetometer [20]. By means of the moving distance and moving direction, the relative displacement can also be estimated accordingly.

III. An Indoor Positioning Algorithm

In this section, an indoor positioning algorithm that fuses a PDR system and an RSS-based Wi-Fi positioning system is proposed. In order to enhance positioning accuracy, the initial user location and moving direction must be determined before executing a fusion algorithm. Therefore, when the positioning or navigation service is requested by a user, the initial location and moving direction of the user are determined sequentially in the first phase, which takes a few seconds. Then, in the second phase, a fusion algorithm is executed. In the rest of this section, the u^{th} user's location estimated by the RSS-based Wi-Fi positioning system is denoted by $L_w^{(u)} = (x_w^{(u)}, y_w^{(u)})$ and the location estimated by the PDR system at the time when $L_w^{(u)}$ is produced is denoted by $L_p^{(u)}= (x_p^{(u)}, y_p^{(u)})$. The user's relative displacement from the beginning estimated by the PDR system at the time when $L_w^{(u)}$ is produced is denoted by l_u. Furthermore, without loss of generality, we suppose that $L_w^{(1)}, L_w^{(2)}, \ldots, L_w^{(\lambda)}$ (and hence $L_p^{(1)}, L_p^{(2)}, \ldots, L_p^{(\lambda)}$) are produced in the first phase. That is, the initial user location and moving direction are determined based on λ Wi-Fi positioning results and relative displacements. The proposed algorithm can be simply presented by a flow chart as shown in Fig. 1.

A. Determination of User's Initial Location and Moving Direction

Since the fluctuation of RSSs is severe in indoor environments, the location estimated by the RSS-based Wi-Fi positioning system may be inaccurate. Hence, the location estimated by the Wi-Fi positioning system cannot be used directly as the initial location of a user. Therefore, a new method is proposed in this paper to determine the initial user location effectively with the aid of the relative displacements estimated by the PDR system.

Refer to Fig. 2. When $L_w^{(1)}$ is estimated and if $L_w^{(1)}$ and l_1 can be estimated accurately, we can infer that the initial

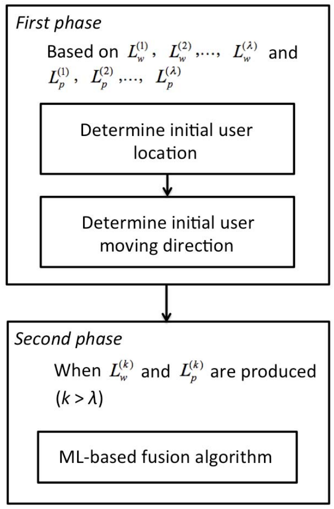

Fig. 1. Flow chart of the proposed algorithm.

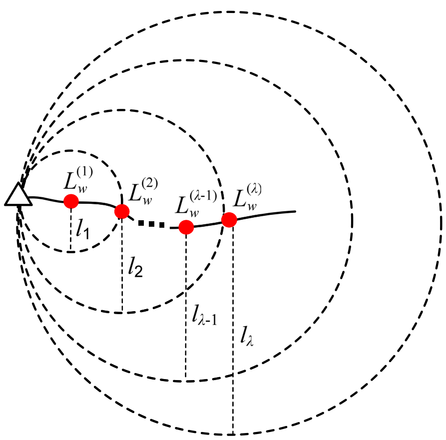

Fig. 2. Determination of the initial user location.

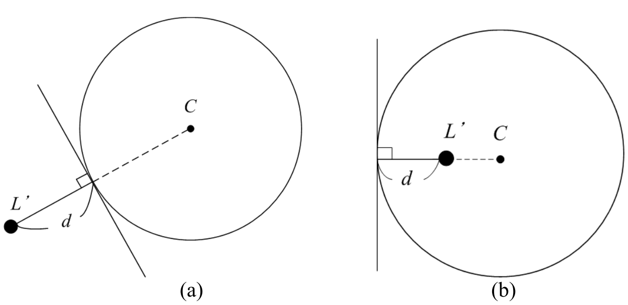

Fig. 3. The distance from a location L' to a circle C when (a) L' is outside C and (b) L' is inside C.

location of the user is located at the circumference with the center $L_w^{(1)}$ and radius l_1. Similarly, when $L_w^{(2)}$ is estimated and if $L_w^{(2)}$ and l_2 can be estimated accurately, according to $L_w^{(2)}$ and l_2, we can also infer that the initial location of the user is located at the circumference with the center $L_w^{(2)}$ and radius l_2. Therefore, when $L_w^{(\lambda)}$ is estimated, theoretically, the initial location of the user is located at the point of tangency, which is made by λ tangent circles. Refer to Fig. 2, where the initial location of the user is estimated at the location of the white triangle.

However, $L_w^{(q)}$ and l_q, $1 \leq q \leq \lambda$, may not be estimated accurately, which results in that the circles may not be tangent. Hence, in the proposed method, when each $L_w^{(q)}$ is estimated, the initial location of the user at that time, denoted by $I^{(q)}=(x_I^{(q)}, y_I^{(q)})$, can be estimated at the location where the total distance from it to the q circles is minimum. The distance from a location to a circle can be defined and illustrated in Fig. 3, where d is the distance from a location L' to a circle C. Therefore, $I^{(q)}$ can be calculated as:

$$\begin{aligned} I^{(q)} &= (x_I^{(q)}, y_I^{(q)}) \\ &= \arg\min_{\alpha,\beta} \sum_{h=1}^{q} \left| \sqrt{(\alpha - x_w^{(h)})^2 + (\beta - y_w^{(h)})^2} - l_h \right|. \end{aligned}$$

To get a more accurate initial location, the initial location of the user is further updated as:

$$\widetilde{I}^{(q)} = \left(\frac{1}{q}\sum_{h=1}^{q} x_I^{(h)}, \frac{1}{q}\sum_{h=1}^{q} y_I^{(h)}\right), \tag{1}$$

which is the arithmetic mean of $I^{(1)}$, $I^{(2)}, \ldots, I^{(q)}$ in Cartesian coordinates.

After finding an initial user location, we can infer the initial moving direction based on the distribution of the Wi-Fi positioning results. Hence, first, given a set of λ Wi-Fi positioning results, i.e., $L_w^{(1)}$, $L_w^{(2)}$, …, $L_w^{(\lambda)}$, a linear regression model is used to find a linear regression function, which can be used to represent the user's moving tendency. Let the linear regression function be:

$$\begin{pmatrix} y_w^{(1)} \\ y_w^{(2)} \\ \vdots \\ y_w^{(\lambda)} \end{pmatrix} = a \times \begin{pmatrix} x_w^{(1)} \\ x_w^{(2)} \\ \vdots \\ x_w^{(\lambda)} \end{pmatrix} + b.$$

The coefficients a and b can be calculated as [23]:

$$a = \frac{(\sum_{h=1}^{\lambda} x_w^{(h)})(\sum_{h=1}^{\lambda} y_w^{(h)}) - \lambda(\sum_{h=1}^{\lambda} x_w^{(h)} y_w^{(h)})}{(\sum_{h=1}^{\lambda} x_w{}^{(h)})^2 - \lambda(\sum_{h=1}^{\lambda} x_w{}^{(h)})^2},$$

$$b = \frac{(\sum_{h=1}^{\lambda} x_w^{(h)} y_w^{(h)})(\sum_{h=1}^{\lambda} x_w^{(h)}) - (\sum_{h=1}^{\lambda} y_w^{(h)})(\sum_{h=1}^{\lambda} x_w^{(h)2})}{(\sum_{h=1}^{\lambda} x_w^{(h)})^2 - \lambda(\sum_{h=1}^{\lambda} x_w{}^{(h)})^2}.$$

Then, referring to Fig. 4, we rotate the trajectory of the user, which is produced by the PDR system, around the initial location $\widetilde{I}^{(\lambda)}$ to choose the most suitable rotational angle so that the total distance from each $L_p^{(q)}$on the trajectory to the linear regression line is minimal, where $1 \leq q \leq \lambda$. The distance from a point (or a location) to a line can be estimated by calculating the distance from the point to the projection of the point on the line. Hence, the initial moving direction of the user is determined.

B. A Maximum Likelihood-Based Fusion Algorithm

As mentioned above, PDR systems can provide continuous tracking, and thus, they can be used to overcome the fluctuation of RSS-based Wi-Fi positioning. However, in the

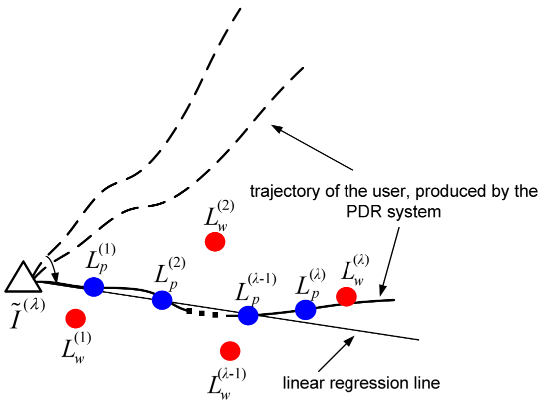

Fig. 4. Determination of the initial moving direction.

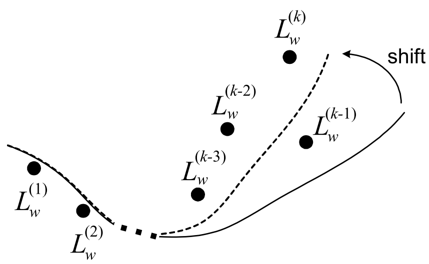

Fig. 5. An example.

PDR system, the cumulative nature of the tracking error increases the difficulty of accurate positioning. How to use Wi-Fi positioning results to correct the deviation of the PDR tracking is worth investigating. Therefore, in this section, an ML-based fusion algorithm is proposed to fuse the PDR and the Wi-Fi positioning systems effectively. We prefer the ML-based fusion scheme to the particle filters, due to the high computational complexity of particle filters, which need to update and maintain the states of a large number of particles whenever a new location is provided.

Refer to Fig. 5. Suppose that $L_w^{(k)}$ is estimated, where $\lambda < k$. The dotted line represents the true moving trajectory. The line represents the trajectory produced by the PDR system, which may deviate from the true moving trajectory over time. The objective of the proposed fusion algorithm is to shift the trajectory produced by the PDR system based on the Wi-Fi positioning results to correct the cumulative tracking error. The fusion algorithm needs to take into account some latest locations that are estimated by the Wi-Fi and the PDR positioning systems (i.e., $L_w^{(k-\varepsilon+1)}, L_w^{(k-\varepsilon+2)}, \ldots, L_w^{(k)}$, and $L_p^{(k-\varepsilon+1)}, L_p^{(k-\varepsilon+2)}, \ldots, L_p^{(k)}$) for the purpose of stable positioning. The fusion algorithm applied to correct tracking errors is described as follows.

Let ϖ denote the mean stride length of a particular user, and θ_f denote the direction of the f^{th} step event. Hence, the displacement of the f^{th} step of the user is estimated as:

$$D_f = (\varpi\ cos\theta_f, \varpi\ sin\theta_f).$$

Let $\ell_{PDR}^{(f)} = (x_{PDR}^{(f)}, y_{PDR}^{(f)})$ denote the PDR-estimated user location after the f^{th} step of the user is detected. After the f^{th} step is detected, the PDR-estimated location is calculated as $\ell_{PDR}^{(f)} = \ell_{PDR}^{(f-1)} + D_f$.

Without loss of generality, we suppose that $L_w^{(k)}$ is the latest location estimated by the Wi-Fi positioning system when the f^{th} step is detected by the PDR system, where $\lambda < k$. Then, an ML-based fusion algorithm is executed for correcting PDR tracking errors, which shifts PDR tracking results appropriately, with the aid of Wi-Fi positioning results. Therefore, based on $L_w^{(k-\varepsilon+1)}, L_w^{(k-\varepsilon+2)}, \ldots, L_w^{(k)}$, and $L_p^{(k-\varepsilon+1)}, L_p^{(k-\varepsilon+2)}, \ldots, L_p^{(k)}$, we want to maximize:

$$\prod_{h=k-\varepsilon+1}^{k} P(L_p^{(h)} + \vartheta_k | L_p^{(h)}, L_w^{(h)}), \tag{2}$$

where $\vartheta_k = (x_\vartheta^{(k)}, y_\vartheta^{(k)})$ represents the shift distance that we want for correcting the PDR tracking errors when $L_w^{(k)}$ is the latest location estimated by the Wi-Fi positioning system. According to Bayes' theorem, we have:

$$\prod_{h=k-\varepsilon+1}^{k} P(L_p^{(h)} + \vartheta_k | L_p^{(h)}, L_w^{(h)}) = \prod_{h=k-\varepsilon+1}^{k} \frac{P(L_p^{(h)}, L_w^{(h)} | L_p^{(h)} + \vartheta_k) \times P(L_p^{(h)} + \vartheta_k)}{P(L_p^{(h)}, L_w^{(h)})}. \tag{3}$$

In (3), $P(L_p^{(h)} + \vartheta_k)$can be assumed to be uniform, and $P(L_p^{(h)}, L_w^{(h)})$ is not affected by the value of $P(L_p^{(h)} + \vartheta_k)$. Hence, the maximization of (2) is equivalent to maximizing the probability of

$$\prod_{h=k-\varepsilon+1}^{k} P(L_p^{(h)}, L_w^{(h)} | L_p^{(h)} + \vartheta_k).$$

Further, since $P(L_p^{(h)} | L_p^{(h)} + \vartheta_k)$ is based on the results of the previous steps and corrections, and $P(L_w^{(h)} | L_p^{(h)} + \vartheta_k)$ is based on the Wi-Fi positioning result, then this is RSS-related. Hence, we can assume that $P(L_p^{(h)} | L_p^{(h)} + \vartheta_k)$ and $P(L_w^{(h)} | L_p^{(h)} + \vartheta_k)$are independent, i.e.,

$$\prod_{h=k-\varepsilon+1}^{k} P(L_p^{(h)}, L_w^{(h)} | L_p^{(h)} + \vartheta_k) = \prod_{h=k-\varepsilon+1}^{k} P(L_p^{(h)} | L_p^{(h)} + \vartheta_k) \times P(L_w^{(h)} | L_p^{(h)} + \vartheta_k).$$

Therefore, the correction is accomplished by finding the most suitable shift distance ϑ_k that maximizes

$$\prod_{h=k-\varepsilon+1}^{k} P(L_p^{(h)} | L_p^{(h)} + \vartheta_k) \times P(L_w^{(h)} | L_p^{(h)} + \vartheta_k).$$

We can determine the value of ϑ_k discretely to search for the maximum. Usually, the Gradient Descent-based search can be applied to reduce the search time. Since it was indicated in [24] that a human movement's speed follows a Gaussian distribution, the values of $P(L_p^{(h)} | L_p^{(h)} + \vartheta_k)$ can be calculated based on the Gaussian likelihood, with mean $(L_p^{(h)} + \vartheta_k)$, and variance σ^2. Similarly, the values of $P(L_w^{(h)} | L_p^{(h)} + \vartheta_k)$ can also

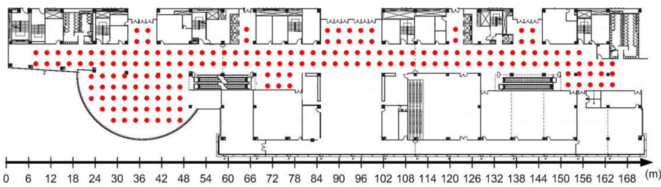

Fig. 6. The fourth floor plane of the Nangang exhibition hall.

be calculated based on the Gaussian likelihood, with mean $(L_p^{(h)} + \vartheta_k)$, and variance σ_*^2. That is:

$$P(L_p^{(h)}|L_p^{(h)}+\vartheta_k) = \frac{1}{\sqrt{2\pi\sigma^2}} \times \exp\{\frac{-|L_p^{(h)} - (L_p^{(h)}+\vartheta_k)|^2}{2\sigma^2}\}$$

and

$$P(L_w^{(h)}|L_p^{(h)}+\vartheta_k) = \frac{1}{\sqrt{2\pi\sigma_*^2}} \times \exp\{\frac{-|L_w^{(h)} - (L_p^{(h)}+\vartheta_k)|^2}{2\sigma_*^2}\},$$

where $|L_p^{(h)} - (L_p^{(h)} + \vartheta_k)|$ represents the distance between $L_p^{(h)}$ and $(L_p^{(h)} + \vartheta_k)$, and $|L_w^{(h)} - (L_p^{(h)} + \vartheta_k)|$ represents the distance between $L_w^{(h)}$ and $(L_p^{(h)} + \vartheta_k)$. The value of σ^2 is determined based on the variance of strides of the user. The value of σ_*^2 is determined based on the variance of $|L_w^{(1)} - L_w^{(2)}|, |L_w^{(2)} - L_w^{(3)}|, \ldots, |L_w^{(k-1)} - L_w^{(k)}|$.

When the most suitable shift distance ϑ_k is found, the values of $L_p^{(h)}$ are updated as $L_p^{(h)} = L_p^{(h)} + \vartheta_k$, for $k - \varepsilon + 1 \le h \le k$. Besides, the PDR-estimated location after the f^{th} step of the user is detected and can be updated as:

$$\ell_{PDR}^{(f)} = \widetilde{I}^{(\lambda)} + \sum_{a=1}^{f} D_a + \sum_{b=\lambda+1}^{k} \vartheta_b, \tag{4}$$

which is also the final estimated location of the user when the f^{th} step is detected. The accuracy of the proposed fusion algorithm will be verified in the next section.

In the process of determining user's initial location, we have to calculate the distance between each RP and u locations produced by the Wi-Fi positioning system, for $u \le \lambda$. The computational complexity in this process is O($r \times \lambda$), where r represents the number of RPs in the system. In the process of determining user's moving direction, suppose that we rotate the trajectory of the user t times, we have to calculate linear regression function t times. The computational complexity in this process is O($t \times \lambda^2$). Since the angle of rotation of the user's trajectory is 5 degrees each time, the value of t is 72(360/5) at most. Likewise, in the fusion algorithm, suppose that we determine the value of ϑ_k t' times, the computational complexity is O($t' \times \varepsilon$). Since the value of λ and ε are small, and the value of ϑ_k is determined discretely, it is easy for the proposed algorithm to achieve real-time positioning.

IV. Experiments

In this section, the performance of the proposed indoor positioning system is evaluated. We use the fingerprint scheme mentioned in Section 2.1 as the Wi-Fi positioning system. Real RSS data are collected by a smartphone (HTC Hero with an Android 1.5 operating system). For an undetected AP, its RSS is set to −95 dBm. Experiments were carried out in a 156-meter × 27-meter area, the fourth floor of the Nangang exhibition hall in Taipei City. Refer to Fig. 6, where there are 24 IEEE 802.11b APs and 183 RPs (denoted by red dots). The sites of the APs are unknown. The distance between every two neighboring RPs is 3 meters. At each RP, there are 100 training RSSs collected from each AP to build the radio map. For the PDR system, we use the accelerometer module and digital compass in the HTC Hero smart phone to track the user. The moving distance produced by the PDR system can be calculated as mentioned in Section II(B).

TABLE I
Comparison of Mean Distance Errors and Standard Deviations for Path 1

	The proposed method	WPF	Zee	fingerprint -ML
Mean distance error (m)	2.76	4.45	6.52	6.56
Standard deviation (m)	2.88	3.51	3.58	4.53

For the Wi-Fi positioning system, during the online stage, the user measures one RSS sample from each AP per 0.1 second. The sampling period is set to one second. That is, a new location of the user from the Wi-Fi positioning system is estimated by analyzing the measured RSSs per one second. Hence, a positioning result from the proposed method can be obtained per one second. The RSSs are measured during working days, when there are many people walking around in the experimental environments.

In our proposed system, when the fusion algorithm is not executed, the locations estimated by the PDR system with the initial user locations estimated by (1) are regarded as the user's locations. When the fusion algorithm is executed, the locations estimated by (4) are regarded as the user's locations. Our experiments compare the performances of our proposed method with the fingerprint scheme using an ML estimator [9] (denoted by fingerprint-ML) and the fusion algorithms in [16] and [18] (denoted by WPF and Zee, respectively). In the following experiments, the initial user location and direction are unknown, except the experiments for WPF, which requires giving the initial user location. The distance error is the distance between the estimated location, denoted by (ϖ_x, ϖ_y), and the real location, denoted by $(\hat{C}_x, \hat{C}_y)$, of the mobile user. That is, the distance error is computed as:

$$\sqrt{(\hat{C}_x - \varpi_x)^2 + (\hat{C}_y - \varpi_y)^2}.$$

For our proposed method, the value of λ must be a parameter of the experiments, because the initial user location is determined based on λ Wi-Fi positioning results and relative displacements to get an accurate result. Fig. 7 shows the accuracies of estimated initial user locations for different values of λ. A small value of λ makes it difficult to correctly infer the initial user location. When the value of λ is larger than five, the accuracy decreases gradually, because the cumulative error from the PDR system increases. Hence, we consider $\lambda = 5$ in subsequent experiments. We set $\varepsilon = 4$.

To verify the positioning accuracy of the proposed method, we set up three different paths in the experiments. Fig. 8

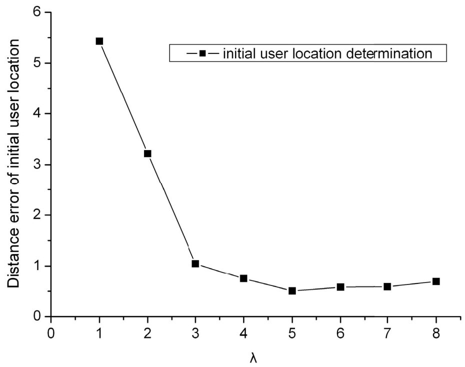

Fig. 7. Mean distance error of initial user location versus value of λ.

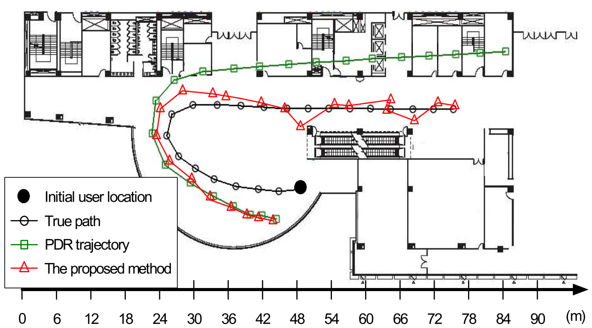

Fig. 8. Path 1.

illustrates the results of experiments in Path 1. The black line represents the true path. The green line represents the PDR trajectory using the initial user location determination method proposed in this paper. The red line represents the trajectory of the proposed method. We can see that the PDR trajectory suffers from cumulative tracking errors, which may increase over time. The proposed method can effectively correct the deviation produced from the PDR system with the aid of the Wi-Fi positioning results.

Table 1 summarizes the mean distance errors and standard deviations of distance errors of different methods in Path 1. As can be seen, the proposed method outperforms the others with reductions in mean distance error and standard deviation by about 35% ~ 58 % and 18% ~ 37%, respectively. Due to the RSS fluctuation, the fingerprint-ML has the largest mean distance error and standard deviation. Since the positioning accuracy of Zee highly depends on the moving behavior of the user, the performances of Zee are not very good. Because the positioning accuracy of WPF is prone to be affected by the unstable results estimated by the Wi-Fi positioning system (i.e., fingerprint-ML in this paper), the performances of WPF are also not very good. Furthermore, WPF requires a known initial user location, which is also unpractical. The proposed method has the smallest mean distance error and standard deviation, and as a consequence, it effectively estimates a tradeoff between the PDR system and the Wi-Fi positioning system according to some latest results of the two systems.

Fig. 9 illustrates the results of experiments in Path 2. The mean distance errors and standard deviations of distance errors of different methods in Path 2 are summarized in

TABLE II

COMPARISON OF MEAN DISTANCE ERRORS AND STANDARD DEVIATIONS FOR PATH 2

	The proposed method	WPF	Zee	fingerprint -ML
Mean distance error (m)	2.57	4.63	7.64	7.10
Standard deviation (m)	2.51	4.68	3.74	4.87

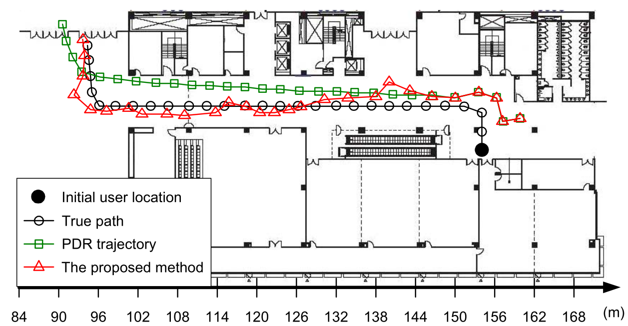

Fig. 9. Path 2.

TABLE III

COMPARISON OF MEAN DISTANCE ERRORS AND STANDARD DEVIATIONS FOR PATH 3

	The proposed method	WPF	Zee	fingerprint -ML
Mean distance error (m)	2.81	5.01	9.15	7.66
Standard deviation (m)	2.73	4.60	4.23	4.82

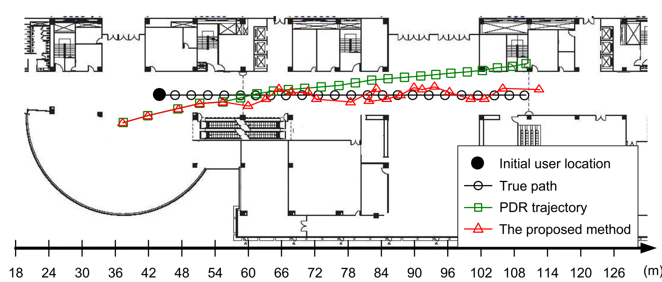

Fig. 10. Path 3.

Table 2. The proposed method is still superior to the other methods. The mean distance error caused by the proposed method is about 45% ~ 66% of the mean distance errors caused by the other methods. The standard deviation caused by the proposed method is about 33% ~ 48% of the standard deviations caused by the other methods. Since the proposed method uses the latest locations estimated by the Wi-Fi and the PDR positioning systems to estimate the user's location for increasing the stability of positioning, it may not quickly reflect the change of the user's moving direction, which can be observed in Fig. 9. Even so, the proposed algorithm can quickly correct the deviation that is caused by changing the moving direction during the next estimates.

Fig. 10 illustrates the results of experiments in Path 3. Similarly, the mean distance errors and standard deviations of distance errors of different methods in Path 3 are summarized in Table 3. The proposed method still performs better than

TABLE IV
MEAN DISTANCE ERROR VERSUS NUMBER OF APs

Number of APs	Mean distance error (m)								
	The proposed method			WPF			Fingerprint-ML		
	Path 1	Path 2	Path 3	Path 1	Path 2	Path 3	Path 1	Path 2	Path 3
24	2.76	2.57	2.81	4.45	4.63	5.01	6.56	7.10	7.66
20	3.36	3.03	3.25	5.25	5.41	5.91	7.98	8.55	9.15
15	4.76	4.21	4.35	7.65	7.52	8.05	11.68	11.53	12.26

the others. Since the user's moving behavior is simple in this experiment, the positioning accuracy of Zee in this experiment is apparently worse than the positioning accuracies of Zee in the previous two experiments, which demonstrates the fact that the positioning accuracy of Zee highly depends on the moving behavior of the user.

The experiment exemplified in Table 4 investigates the influence of the number of APs on the mean distance error for three different methods. As observed, all mean distance errors go up as the number of APs decreases. The proposed method still has the best performance. Since some latest locations estimated by the Wi-Fi and the PDR system are used in the fusion algorithm, the positioning stability is enhanced substantially, and hence, the positioning accuracy increases.

In summary, the proposed method has better positioning results than the others. Actually, the large RSS uncertainty degrades the positioning accuracy of the Wi-Fi positioning system, which can also degrade the positioning accuracy of the proposed method. However, the results from the Wi-Fi positioning system can still be used to successfully bind the cumulative PDR tracking error. If there is no Wi-Fi positioning system to bind the PDR tracking error, the positioning results become worse and worse as the positioning results of Zee, in which the Wi-Fi signal strengths are only used to constrain the initial user location.

V. CONCLUSION

An indoor positioning service is very important for mobile and ubiquitous computing. Inertial sensors, which are nowadays embedded in hand-held devices such as smart phones, can be used for real-time pedestrian tracking. The PDR system uses inertial sensors to track a user. One of the main challenges for pedestrian tracking using a PDR system is that the tracking error accumulates over time. Since WLAN-based indoor positioning systems are more and more popular due to the wide availability and ubiquitous coverage of IEEE 802.11 WLANs in indoor environments, in this paper, a maximum likelihood-based fusion algorithm that integrates a typical Wi-Fi indoor positioning system with a PDR system is suggested to eliminate the cumulative tracking error without requiring the information of initial user location and direction in advance. The fusion algorithm takes into account some of the latest locations from the two different positioning systems for the purpose of positioning stability.

To demonstrate that the proposed method can be used in practice, the experiments were carried out in the Nangang exhibition hall of Taipei City. Experimental results show that the proposed positioning algorithm is superior to the previous positioning algorithms in positioning accuracy and stability.

REFERENCES

[1] [Online]. Available: http://www.gps.gov/

[2] E. Hepsaydir, "Mobile positioning in CDMA cellular networks," in *Proc. IEEE Veh. Technol. Conf.*, vol. 2. 1999, pp. 795–799.

[3] R. Yamamoto, H. Matsutani, H. Matsuki, T. Oono, and H. Ohtsuka, "Position location technologies using signal strength in cellular systems," in *Proc. IEEE Veh. Technol. Conf. (VTC)*, vol. 4. 2001, pp. 2570–2574.

[4] A. Smailagic and D. Kogan, "Location sensing and privacy in a context-aware computing environment," *IEEE Wireless Commun.*, vol. 9, no. 5, pp. 10–17, Oct. 2002.

[5] D. Niculescu and N. Badri, "Ad hoc positioning system (APS) using AOA," in *Proc. IEEE Int. Conf. Comput. Commun.*, vol. 3. Apr. 2003, pp. 1734–1743.

[6] L. Xinrong and K. Pahlavan, "Super-resolution TOA estimation with diversity for indoor geolocation," *IEEE Trans. Wireless Commun.*, vol. 3, no. 1, pp. 224–234, Jan. 2004.

[7] P. Bahl and V. N. Padmanabhan, "RADAR: An in-building RF-based user location and tracking system," in *Proc. IEEE Int. Conf. Comput. Commun.*, vol. 2. Mar. 2000, pp. 775–784.

[8] M. A. Youssef, A. Agrawala, and A. U. Shankar, "WLAN location determination via clustering and probability distributions," in *Proc. IEEE Int. Conf. Pervas. Comput. Commun.*, Mar. 2003, pp. 143–150.

[9] M. Brunato and R. Battiti, "Statistical learning theory for location fingerprinting in wireless LANs," *Comput. Netw.*, vol. 47, no. 6, pp. 825–845, Apr. 2005.

[10] F. Chen, W. S. A. Au, S. Valaee, and T. Zhenhui, "Compressive sensing based positioning using RSS of WLAN access points," in *Proc. IEEE Int. Conf. Comput. Commun.*, Mar. 2010, pp. 1–9.

[11] A. Kushki, K. N. Plataniotis, and A. N. Venetsanopoulos, "Kernel-based positioning in wireless local area networks," *IEEE Trans. Mobile Comput.*, vol. 6, no. 6, pp. 689–705, Jun. 2007.

[12] S.-H. Fang, T.-N. Lin, and K.-C. Lee, "A novel algorithm for multipath fingerprinting in indoor WLAN environments," *IEEE Trans. Wireless Commun.*, vol. 7, no. 9, pp. 3579–3588, Sep. 2008.

[13] Z.-L. Wu, C.-H. Li, J. K.-Y. Ng, and R. P. H. Leung, "Location estimation via support vector regression," *IEEE Trans. Mobile Comput.*, vol. 6, no. 3, pp. 311–321, Mar. 2007.

[14] S.-P. Kuo and Y.-C. Tseng, "A scrambling method for fingerprint positioning based on temporal diversity and spatial dependency," *IEEE Trans. Knowl. Data Eng.*, vol. 20, no. 5, pp. 678–684, May 2008.

[15] H. Wang, H. Lenz, A. Szabo, J. Bamberger, and U. D. Hanebeck, "WLAN-based pedestrian tracking using particle filters and low-cost MEMS sensors," in *Proc. IEEE Workshop Posit., Navigat. Commun.*, Mar. 2007, pp. 1–7.

[16] F. Evennou and F. Marx, "Advanced integration of WiFi and inertial navigation systems for indoor mobile positioning," *EURASIP J. Appl. Signal Process.*, 2006, pp. 1–11.

[17] O. Woodman and R. Harle, "Pedestrian localisation for indoor environments," in *Proc. ACM Int. Conf. Ubiquitous Comput.*, 2008, pp. 114–123.

[18] A. Rai, K. K. Chintalapudi, V. N. Padmanabhan, and R. Sen, "Zee: Zero-effort crowdsourcing for indoor localization," in *Proc. ACM Int. Conf. Mobile Comput. Netw.*, 2012, pp. 293–304.

[19] A. R. J. Ruiz, F. S. Granja, J. C. P. Honorato, and J. I. G. Rosas, "Accurate pedestrian indoor navigation by tightly coupling foot-mounted IMU and RFID measurements," *IEEE Trans. Instrum. Meas.*, vol. 61, no. 1, pp. 178–189, Jan. 2012.

[20] 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. Inform.*, vol. 7, no. 3, pp. 455–466, Aug. 2011.

[21] H. Wang, S. Sen, A. Elgohary, M. Farid, M. Youssef, and R. R. Choudhury, "No need to war-drive: Unsupervised indoor localization," in *Proc. ACM Int. Conf. Mobile Syst., Appl., Services*, 2012, pp. 197–210.

[22] P. M. Djuric *et al.*, "Particle filtering," *IEEE Signal Process. Mag.*, vol. 20, no. 5, pp. 19–38, Sep. 2003.

[23] D. M. Bates and D. G. Watts, *Nonlinear Regression Analysis and its Applications*, 1st ed. New York, NY, USA: Wiley, 1988.

[24] T. S. Azevedo, R. L. Bezerra, C. A. V. Campos, and L. F. M. de Moraes, "An analysis of human mobility using real traces," in *Proc. IEEE Wireless Commun. Netw. Conf.*, Apr. 2009, pp. 1–6.

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