AiFiMatch: Accurate Indoor Map Matching Algorithm Based on Activity Detection and Crowd-sourced Wi-Fi

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Abstract. Map matching has been widely investigated in indoor pedestrian navigation to improve positioning accuracy and robustness. In this paper, we present AiFiMatch: a map matching algorithm that can provide accurate pedestrian walking trajectory tracking based on Hidden Markov model (HMM) for smartphone users. AiFiMatch abstracts the indoor map using a directed graph model in which the location-related activities, such as turn, walking stairs, taking the elevator, are directed edges, indoor road segments between these special locations are nodes. With the help of a novel HMM model, AiFiMatch maps pedestrian's walking trajectory subset sequence to indoor map based on activity detection (AD). Simultaneously, Wi-Fi fingerprints can be bound to physical locations by timestamp. AiFiMatch can automatically construct and update radio map of indoor road segments via crowdsourcing. With this radio map, AiFiMatch efficiently solves the multiple hypotheses problem. We have evaluated our proposed algorithm using smartphones in the fifth floor of a teaching building on campus. Experimental results show that AiFiMatch can accurately track a pedestrian even without knowing the initial position and is robust to a certain degree of step length and heading direction estimation errors in the experimental environment. The mean offline positioning error is about 1.24 m. The results also demonstrate that AiFiMatch significantly improves the convergence speed in buildings with Wi-Fi infrastructure.

Keywords: Map Matching · Hidden Markov Model · Activity Detection · Crowdsourced Wi-Fi.

1 Introduction

Location based services (LBS) have spilled over into all aspects of people's daily life. Outdoors, global positioning system (GPS) is able to provide a reasonably good positioning [1]. However, robust and effective indoor pedestrian positioning is still at its infancy due to the blockage of GPS signals.

It is common for indoor positioning schemes to leverage on pre-installed infrastructure like Wi-Fi[2], UWB[3], RFID[4], Bluetooth[5], and so on. These systems offer absolute positioning with a limited error level,but rely on expensive hardware or time-consuming pre-training. At present, motion sensors, including accelerometer, gyroscope and magnetometer, are widely used in smartphones. Therefore, dead reckoning (DR) techniques using motion sensors are another way for indoor positioning, which derive the current position by adding the estimated displacement to the previous one. DR techniques are known as pedestrian dead reckoning (PDR) for pedestrian tracking and positioning [6–8]. The PDR technique itself does not provide a final solution to the pedestrian positioning problem and another technique is required to provide the initial position estimates.

The positioning error of PDR technique mainly comes from step length and direction estimation errors and even small errors will be magnified by cumulation over time. Indoor map information may be connected with PDR, namely map matching algorithm [9]. Several map matching algorithms have been proposed to constrain the cumulative errors [8–12]. One algorithm uses activity-related locations as virtual landmarks to find the optimal trajectory of a pedestrian. The activity-related locations are special locations of a building, such as an elevator, a stair, a corner, and so on. When a pedestrian passes these locations, the pedestrian's activities can be distinguished from normal walking. Human activity detection (AD) algorithms based on smartphones have attracted more and more researchers' attention in the past decade. Given the symmetry of indoor environment, activity-based map matching algorithms fails since there may be more than one alternatives for the same activity feature or activity sequence [8].

Crowdsourcing is a low-cost and efficient way to extract useful information from data acquired by crowd participants [13]. The crowdsourcing method has been successfully applied to construct Wi-Fi fingerprint database [14, 15]. At present, Wi-Fi access points (AP) have been widely developed in public buildings. Meanwhile, almost all smartphones are equipped with Wi-Fi interfaces. Hence, It is feasible to introduce Wi-Fi signal feature, such as received signal strength (RSS), into map matching algorithms [16, 17] to improve the positioning performance. Furthermore, Wi-Fi RSS can be used as a new feature to deal with the multiple hypotheses problem due to the symmetry of indoor environments.

We therefore propose AiFiMatch: a novel hidden markov model (HMM) based map matching algorithm, which integrates activity-based map matching and crowdsourced Wi-Fi. During pedestrians walking, many smartphones can simultaneously collect motion sensors' data and Wi-Fi received signal strength (RSS) values. On the one hand, AiFiMatch uses motion sensors' data to detect the pedestrian's location-related activities, divides the walking trajectory into sub-trajectory sequence and realizes pedestrian positioning based on PDR even without knowing the initial position by matching the sub-trajectory sequence to indoor road map. On the other hand, according to map matching results, WiFi RSS fingerprints can be bound to physical locations. As time goes by, a Wi-Fi fingerprint database can be built even further by crowdsourcing. This paper defines the dissimilarity between Wi-Fi RSS sequences. With the help of crowdsourced Wi-Fi fingerprint database, this dissimilarity can be used to reduce the number of candidate hidden states in the presented HMM model and even eliminate the symmetry of indoor environment. Thus, AiFiMatch can get the pedestrian's position estimations within a short time delay.

The remainder of this paper is organized as follows: Section II reviews the related work in the literature. Section III gives an overview of the AiFiMatch system and its preprocessing components. Then, we detail the proposed HMM-based map matching algorithm in Section IV. Section V shows the experimental results and analysis of the AiFiMatch system. Finally, Section VI concludes this paper.

2 Related Work

PDR techniques relying on smartphones have attracted much attentions in the past few years, but we only position the literature with respect to our work in this section. We focus on techniques that utilize easily accessible infrastructure, such as indoor map information, inertial sensors embedded in smartphones and wireless access points in buildings. We divide these techniques into the following three categories: map information assisted PDR, activity detection based PDR and combination PDR with Wi-Fi Fingerprint.

2.1 Map Information Assisted PDR

The pedestrian motion trajectory is restricted by the indoor map, therefore, it is an opportunity to improving PDR using map information. Woodman and Harle proposed a pedestrian positioning approach which combines a detailed building map model and a particle filter to provide absolute positioning [18]. An improved particle filter is also introduced into map matching in [19] and its computational complexity is less than traditional ones. Map matching algorithm is triggered only when a pedestrian is considered walking along a certain corridor. [20] leverages the topology of the indoor map to filter out infeasible locations over time with the particle filter. However, the computation time is still the major issues of particle filter based map matching algorithms, as a large number of particles are required to ensure good estimations. MapCraft proposed in [21] expresses the map matching based pedestrian positioning problem as a conditional random field (CRF), which is extremely computationally efficient and tracks well even when presented with very noisy sensor data. Both MapCraft and our work only requires a floor plan to track pedestrians, but a crowd-sourced Wi-Fi fingerprints database could be built by our work when wireless access points exist.

2.2 Activity Detection based PDR

An activity detection based PDR system limits the cumulative errors by recognizing pedestrians' activities and matching their activities to corresponding locations. A random forest classifier is applied to classify consecutive activities relevant to positioning in multi-floor buildings in [22], such as walking, stairs up and stairs down. To prevent cumulation of PDR errors, inertial sensor features are used as virtual landmarks to match the special locations of positioning areas [23]. However, the ambiguity of the virtual landmark is not considered. In [8], a HMM model is used to match the activity sequence of smartphone user to the corresponding landmarks of indoor map. This approach can avoid the mismatch problem caused by the ambiguity of the virtual landmark. The hidden states and observations from the HMM model are different from the one presented in this work. We implement this approach and compare it with our work based on our own experimental data. SemanticSLAM proposed in [11] discovers semantic landmarks in a crowd-sensing approach based on the data collected from the smartphone users. A semantic landmark is defined by two attributes: its sensors pattern and physical location. Each sensors pattern corresponds to one kind of activity of the smartphone users in buildings. ALIMC [10] uses the activity-related location as the landmark to merge the crowdsourcing trajectories. This approach can automatically construct indoor maps without any prior knowledge. All these SLAM approaches can be viewed as map generators providing digital indoor maps to our map matching algorithm.

2.3 Combination PDR with Wi-Fi Fingerprint

Wireless access points are widely developed these days in many buildings and Wi-Fi fingerprinting is a well-known localization technique. Combination PDR with Wi-Fi fingerprint tries to avoid the disadvantages of either of the two approaches. WiFi-SLAM [24] is a pioneer in fusing Wi-Fi RSS and motion sensor data. It simultaneously build a map of the environment and locate the user within this map. A modified HMM model for the fusion of Wi-Fi fingerprinting and PDR is presented in [25]. For this approach, a pre-trained Wi-Fi fingerprint database is required. HiMLoc [26] integrates PDR with indoor landmarks detection and Wi-Fi fingerprinting by a distributed particle filter. In spite of computational complexity, this approach, like our work, can provide continuous update of the training set of Wi-Fi fingerprints.

3 AiFiMatch Overview

AiFiMatch is an activity-based map matching system to pedestrian dead reckoning problem. In this section, we first provide an overview of the AiFiMatch system and then describe the details of its preprocessing components including PDR implementation based on smartphone, activity detection and indoor floor plan abstraction. We leave the details of the core of AiFiMatch system, the HMM based map matching module, to the next section.

3.1 Architecture Overview

The overall architecture of the AiFiMatch system is shown in Fig. 1. The input to the system is a indoor floor plan and time-stamped sensor data including motion data and Wi-Fi fingerprint. AiFiMatch utilizes embedded sensors of a smartphone to simultaneously collect motion data and Wi-Fi RSS values while the indoor floor plan can be manually entered or generated by crowdsourcing based indoor map construction algorithm.

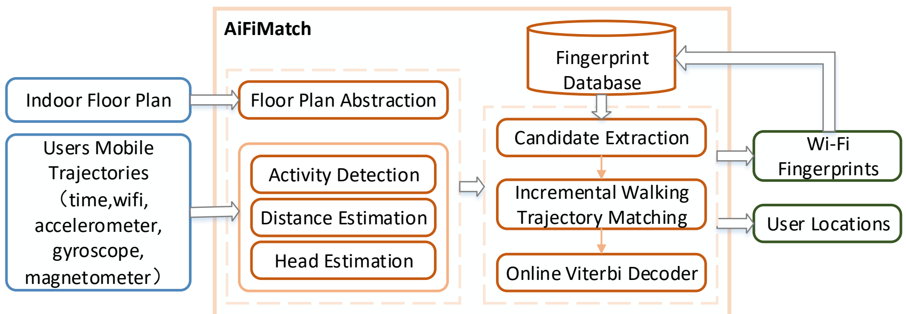


Fig. 1. AiFiMatch System Architecture.

Firstly, AiFiMatch starts by indoor floor plan abstraction to create a directed graph to facilitate the map matching model establishment. Secondly, the system estimates the walking distance and heading direction with data of motion sensors. Finally, location-related activities are detected with the pre-trained decision tree, and then the pedestrian's trajectory data including motion data and Wi-Fi RSS values are divided into trajectory subsets sequence.

The directed graph of indoor floor plan and walking trajectory subsets sequence are then passed to the HMM based map matching module whose outputs include the pedestrian position estimations and Wi-Fi fingerprints. These Wi-Fi fingerprints can be used to update indoor radio map. Our proposed HMM based map matching module contains three sub-modules: Candidate Extraction, Incremental Walking Trajectory Matching and an Online Viterbi Decoder. The Candidate Extraction module determines the candidate road segments from the directed graph of indoor floor plan that satisfy the spatial and Wi-Fi signal conditions. The module takes into account the errors of pedestrian heading direction estimation and the previous bound Wi-Fi fingerprint. The Incremental Walking Trajectory Matching module integrates a number of modifications to the standard HMM based map matching algorithm to take walking trajectory subsets sequence into account as well as the detected activities to enhance the accuracy of the estimated indoor road paths. Finally, the Online Viterbi Decoder uses dynamic programming to efficiently determine the most probable indoor road segments sequence.

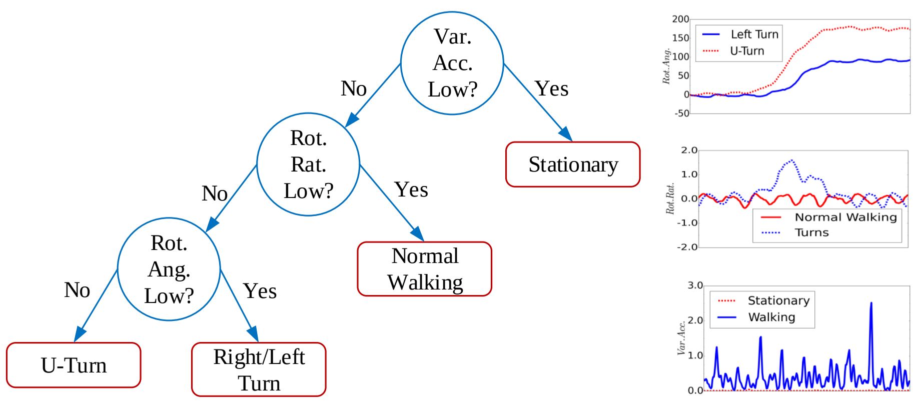
3.2 Preprocessing

In the balance of this section, we give the details of three preprocessing components and leave the details of the map matching and Wi-Fi enhancement algorithm to the next section.

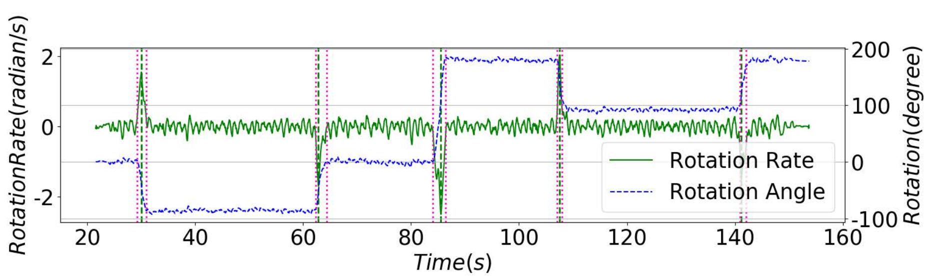
PDR Implementation Based on Smartphone: PDR is a positioning scheme that derives the current position by adding the estimated displacement to the previous one based on motion sensors carried by smartphones. In PDR scheme, the pedestrian's position is usually updated by the step and the heading direction during one step is supposed to be unchanged. The pedestrian's position after $k-1$ steps can be denoted as (x_{k-1}, y_{k-1}). The k-th step length and heading direction are denoted as sl_k and θ_k, respectively. Then, the pedestrian's position after k steps can be obtained by the following equation:

$$\begin{pmatrix} x_k \\ y_k \end{pmatrix} = \begin{pmatrix} x_{k-1} + sl_k \cdot \sin\theta_k \\ y_{k-1} + sl_k \cdot \cos\theta_k \end{pmatrix} \tag{1}$$

The heading direction is measured by the fusion of gyroscope and magnetometer. The step length and step count estimate approach is out of scope of this paper and can be found in [27].



(a) *Decision Tree for Activity Detection*



(b) *Turning Activity Detected Example*

Fig. 2. Decision Tree for Activity Detection and An Example

Activity Detection: In this paper, AiFiMatch considers four types of pedestrian activities: stationary, normal walking, turning at a corner (left or right turn) and turning around (U-turn), which would occur on the flat ground. The decision tree for activity detection and signal features of each activity is shown in Fig. 2a. The top level separates walking and stationary based on the variance of the accelerometer. With the help of gyroscope, the second level uses the rotation rate to separate the normal walking and turns while the third level separates the U-turn case from the left or right turn case based on the rotation angle during the turning. Three participants with different brands of smartphones were asked to complete three activities (U-turn, left and right turn) in our experimental environment. The sample size of each activity was 60 traces. Fig. 2b shows an example for turning activity detection and the activity detection result is summarized in Table 1.

Table 1. Confusion Matrix of Activity Detection

Activity Type	Left Turn	Right Turn	U-turn	No Type
Left Turn	58	0	0	2
Right Turn	0	59	0	1
U-turn	0	0	60	0

Indoor Floor Plan Abstraction: In the indoor environment, there are many activity-relative locations such as corridor corners and entrances of rooms where pedestrians may perform different activities other than normal walking. These special locations divide the indoor roads into segments. With road segments as nodes in the form of *(coordinate of first endpoint* (x_1, y_1)*, accessible direction of first endpoint* (φ_1)*, coordinate of second endpoint* (x_2, y_2)*, accessible direction of second endpoint* (φ_2)*)*, the activity type from one road segment to another as directional edges in the form of *(Activity Type (AT))*, the indoor floor plan would be represented as a direction graph. Fig. 3 shows an example of indoor floor abstraction.

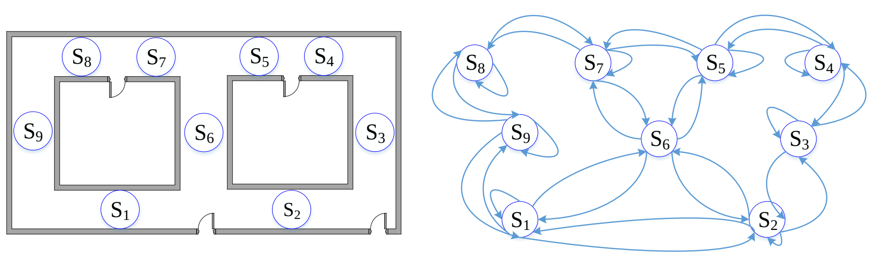


Fig. 3. Floor Plan Abstraction Example.

4 HMM based Map Matching Algorithm

Through this section, we detail the HMM based map matching module of AiFi-Match system. We first start by providing the novel HMM model and the details of its components. Then, we describe the Wi-Fi enhancement algorithm for our proposed HMM model.

4.1 Hidden Markov Model

Taking computing power and energy limit of a smartphone into account, our proposed map matching algorithm select HMM to match the pedestrian's trajectory subsets sequence to the directed graph of indoor floor plan. A HMM can be represented as $\lambda = (S, V, A, B, \pi)$, where:

1) $S = \{s_1, s_2, s_3, \ldots, s_N\}$ is the set of possible states and $N = |S|$. In our case, each state represents an indoor road segment, that is, a node of the directed graph. Therefore, a state s is represented by the ordered tuple in the form of $(id, x_1, y_1, \varphi_1, x_2, y_2, \varphi_2)$, where id is the identification of road segment, x_1, y_1, φ_1, x_2, y_2 and φ_2 are different attributes of node of the directed graph, respectively. $s.leng$ denotes the length of road segment and can be obtained from the coordinates of two endpoints of this road segment. *Note that two or more road segments connected by a straight line can form new states (Fig. 4).*

2) $V = \{v_1, v_2, v_3, \ldots, v_M\}$ is the set of observations from the model and $M = |V|$. For each walking trajectory of a pedestrian, PDR technique gives displacement and heading direction estimations. However, due to the interference of many kinds of metal materials to the magnetic field in buildings, the heading direction estimation has a large error. Therefore, in our case, each observation is a displacement estimation and is represented by *(dist)*.

3) $A = \{a_{ij}\}$ is the state transition probability distribution, where $a_{ij} = p\left\{q_{t+1} = s_j | q_t = s_i\right\}, i, j \leq N$, where q_t denotes the state at time t. In our case, the transition probability a_{ij} is the probability of walking to the next road segment $s_{j,t}$ given the current road segment is $s_{i,t-1}$. Intuitively, for probable transition between two road segments, the pedestrian's activity should match the activity type between the same two segments. Therefore, given the detected activity of a pedestrian $Ped_{AT}(t)$ at time t and the activity type between two segments ${Seg_{AT}}^{ij}$, AiFiMatch models this intuition by the equation 2, where $p(Ped_{AT}(t)|{Seg_{AT}}^{ij})$ can be found in confusion matrix.

$$p(s_{j,t}|s_{i,t-1}) = p(s_j|s_i, Ped_{AT}(t)) = p(Ped_{AT}(t)|{Seg_{AT}}^{ij}) \tag{2}$$

4) $B = \{b_i(k)\}$ is the observation probability distribution in state i, where $b_i(k) = p\{o_t = v_k|q_t = s_i\}, 1 \leq i \leq N, 1 \leq k \leq M$ and o_t, q_t are the observation and state at time t, respectively. Observation probabilities also called emission probabilities represent the likelihood that a measurement resulted from a given state. In our case, given a displacement observation $v_k.dist(t)$, there is an emission probability $p(v_k.dist(t)|s_i.leng)$ for each candidate road segment s_i, where $s_i.leng$ denotes the length of road segment s_i which can be obtained from the coordinates of two endpoints of this road segment. If a pedestrian has passed the complete road segment s_i, AiFiMatch models the emission probability as a Gaussian Distribution:

$$f_1(\mathrm{v_k.dist(t),s_i.leng}) = \frac{1}{\sqrt{2\pi}\sigma_d} e^{-\frac{(v_k.dist(t)-s_i.leng)^2}{2{\sigma_d}^2}} \tag{3}$$

where σ_d is the standard deviation of the measured displacement. Based on the distance calculation method of PDR, the displacement is in direction proportion to step length. Therefore, σ_d can be obtained based on the standard deviation of step length σ_s. Considering the situation that a pedestrian is walking on the road segment, all long enough candidate road segments should have the same probability, AiFiMatch models the situation using the equation as:

$$f_2(\mathrm{v_k.dist(t),s_i.leng}) = \frac{1}{\sqrt{2\pi}\sigma_d} e^{-4.5}, v_k.dist(t) + 3\sigma_d \leq s_i.leng \tag{4}$$

Hence, the final emission probability, $p(v_k|s_i)$, is modeled as:

$$p(v_k|s_i) = f(v_k.dist(t), s_i.leng) = \begin{cases} \frac{1}{\sqrt{2\pi}\sigma_d} e^{-4.5}, v_k.dist(t) + 3\sigma_d \leq s_i.leng \\ \frac{1}{\sqrt{2\pi}\sigma_d} e^{-\frac{(v_k.dist(t) - s_i.leng)^2}{2\sigma_d{}^2}}, otherwise \end{cases} \tag{5}$$

5) $\pi = \{\pi_i\}$ is the initial state distribution, where $\pi_i = p\{q_1 = S_i\}, 1 \leq i \leq N$. If the starting point or the first road segment is known, the initial state distribution is 1 since the first road segment is the only candidate; otherwise, all candidate road segments are selected by the *Candidate Extraction* module and the initial state distribution is uniform in all candidates. Let S_c denote the set of all candidates, and the initial state distribution is re-estimated after each step by the equation 6 until the first location-related activity is detected.

$$\pi_{i,t} = \pi_{i,t-1} \cdot f(v_k.dist(t), s_i.leng), s_i \in S_c \tag{6}$$

4.2 Candidate Extraction

AiFiMatch uses the heading direction of a pedestrian and Wi-Fi fingerprint to select the candidate states. Here, we describe the extraction algorithm by heading direction and leave the Wi-Fi fingerprint extraction algorithm to the *Wi-Fi Enhancement* Section.

Intuitively, the heading direction of a pedestrian should match the direction of road segment. Therefore, AiFiMatch models the direction difference by the following function to select the candidates:

$$g_1 = g_1(Ped_{dir}, s) = \begin{cases} 1, if\, |Ped_{dir} - s.\varphi_j| < H_{TH}, j = 1, 2 \\ 0, otherwise \end{cases} \tag{7}$$

where Ped_{dir} denotes the heading direction of a pedestrian, s is a state, H_{TH} is the threshold for candidate extraction, which is set to *55 (degree)* based on the experiments.

4.3 Wi-Fi Enhancement

Map matching offers an important source of information and an excellent way to improve the position estimations, especially in narrow corridors, but it has some limitations when the indoor environment presents symmetries that generates multiple hypotheses. Supposing that a pedestrian walks along this segments sequence (s_3, s_4, s_5, s_6), as shown in Fig. 4, for the given observable states, it is directly to be seen that the segments sequence (s_6, s_7, s_8, s_9) may have almost the same matching probability as the actual one. In this situation, traditional HMM based map matching algorithm fails [8].

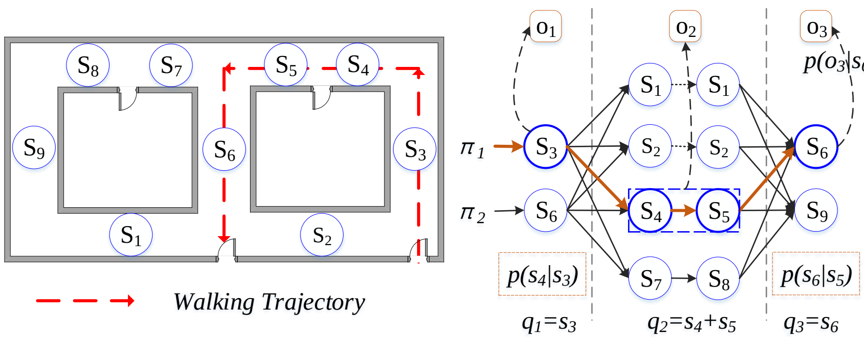


Fig. 4. Illustration of the Viterbi Decoding.

AiFiMatch introduces Wi-Fi dissimilarity to distinguish multiple hypotheses due to the symmetry of building structure. After AiFiMatch determines a pedestrian's walking trajectory by the Online Viterbi Algorithm [9], the pedestrian's positions can be derived by PDR using the two endpoints of determined segments as the starting point. Therefore, Wi-Fi fingerprints collected synchronously during the pedestrian walking can be bound to the corresponding positions by time alignment and then update the Wi-Fi fingerprint database of indoor environment where the pedestrian is located. In order to improve the HMM based map matching algorithm described above, the paper not only binds Wi-Fi fingerprints to physical positions but also road segments. All Wi-Fi fingerprints of one road segment are sorted in the road segment's direction. For two fingerprints f_x, f_y, and MAC address set of their Access Points X, Y, define dissimilarity J_δ between f_x, f_y as follows:

$$J_\delta(f_x, f_y) = 1 - J(X, Y) = \frac{|X \cup Y| - |X \cap Y|}{|X \cup Y|} \tag{8}$$

where equation 8 is known as Jaccard distance. With this dissimilarity of two fingerprints, we define the similarity function $L(S_a, S_b)$ between two fingerprint sequences $S_a = (f_1^a, f_2^a, \cdots, f_w^a)$, $S_b = (f_1^b, f_2^b, \cdots, f_k^b)$:

$$\begin{aligned} L(S_a, S_b) = \min(&\tfrac{1}{w}\sum_{t=1}^{w} J_\delta({f_t}^a, {f_{i+t}}^b), 0 \le i \le k - w, \\ &\tfrac{1}{w}\sum_{t=1}^{w} J_\delta({f_t}^a, {f_{j-t}}^b), w + 1 \le j \le k + 1) \end{aligned} \tag{9}$$

where $w = |S_a|$, $k = |S_b|$ and $2 < w < k$. Given segment candidate set G and the set R of all road segments bound with Wi-Fi fingerprints sequence, Finally, AiFiMatch models the dissimilarity of two Wi-Fi fingerprint sequences and the different stages of fingerprint database by the following function to select the candidates:

$$g_2 = g_2(S_{ped}, S_i) = \begin{cases} 0, if\, i \neq \arg\min_j \{L(S_{ped}, S_j), S_j \in G, G \subseteq R\} \\ 0, if\, \min\{L(S_{ped}, S_i),\ S_i \in G \cap R\} > d \\ 1, otherwise \end{cases} \tag{10}$$

where d is the threshold to distinguish two Wi-Fi fingerprint sequences.

A pilot study is conducted to evaluate the dissimilarities between two fingerprint sequences of same and different road segments. A prototype installed in three smartphones (360 N5, OPPO R827T and Xiaomi 3W) is used to collect Wi-Fi RSS values at 1Hz. Each participant was asked to walk along two symmetric road segments in two directions. The participant with 360 N5 smartphone was asked to repeat 12 times while the others were asked to repeat 6 times. Among them, 6 Wi-Fi data collected by 360 N5 smartphone were used as Wi-Fi fingerprint database, while other Wi-Fi data were used as online Wi-Fi fingerprint sequences. The maximum and minimum dissimilarities between fingerprint sequences of same and different road segments are shown in Fig. 5. From Fig. 5, with increases in the length of Wi-Fi fingerprint sequence w, the dissimilarity between two sequences of same segments gradually decreases, while the dissimilarity between two sequences of different segments gradually increases. Considering the device diversity, in order to avoid missing the correct alternative segments, the minimum value of the threshold d is 0.773.

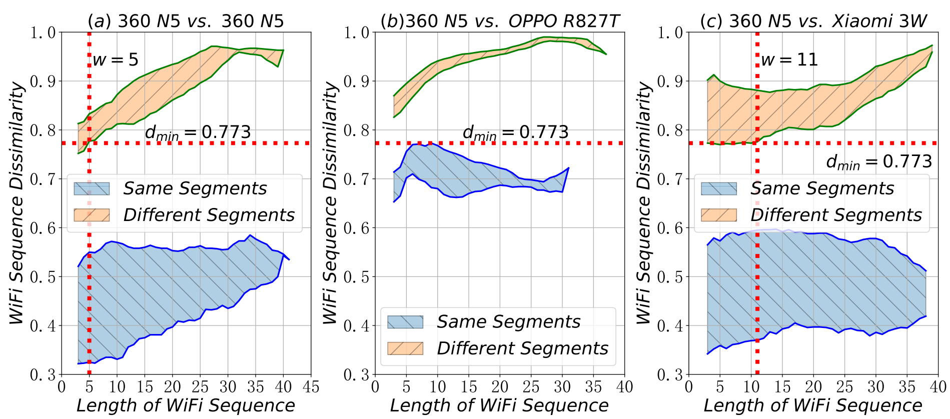


Fig. 5. Dissimilarity between Two Wi-Fi Fingerprint Sequences from Multiple Devices.

4.4 Optimal State Sequence Estimation

Once the HMM parameters are estimated, we can user the Viterbi algorithm to get the most probable hidden states sequence $Q = (q_1, q_2, ..., q_k)$ for a given observation sequence $O = (o_1, o_2, ..., o_k)$. A Viterbi variable $\delta_t(i)$ is defined by equation 11 to represent that, at time t, the HMM model reaches the hidden state s_i along a certain path and outputs the maximum probability.

$$\delta_t(i) = max\{p(q_1, q_2, ..., q_t = s_i, o_1, o_2, ..., o_t|\lambda)\} \tag{11}$$

At time $t+1$, the maximum probability reaching the hidden state s_j can be recursively derived from the Viterbi variable at time t by the following equation.

$$\delta_{t+1}(j) = [\max_i\{\delta_t(i) \cdot p(q_{t+1} = s_j|q_t = s_i)\}] \cdot p(o_{t+1}|q_{t+1}), 1 \le t \le k \tag{12}$$

For AiFiMatch to operate in real-time, it cannot wait until the whole sequence is available. Hence, The online Viterbi algorithm [28] is applied to compute the maximum likelihood sequence of states using dynamic programming. AiFiMatch users Viterbi algorithm in an incremental manner. Every time a new step of a pedestrian is detected, the HMM parameters are calculated for the new introduced sensors data and the associated candidate states. Fig. 4 illustrates the proposed HMM model Viterbi decoding. The decoded sequence is colored in blue.

During the beginning process of the algorithm, if the number of states is too small, the most probable states sequence is not always the correct one, especially when the starting point of pedestrian is unknown. Therefore, we give a criteria by the equation $c = p_{fir}/p_{\sec}$ to determine the status of this algorithm, where p_{fir} is the highest probability of the states sequence and $p_{\sec}$ is the second highest probability of the states sequence. We set a threshold, if c is greater than or equal to the threshold, we choose the Viterbi decoding result. The selected hidden states sequence represents the pedestrian's passed indoor road segments.

AiFiMatch algorithm is summarized with the pseudocode in Algorithm 1.

Algorithm 1 AiFiMatch online map matching algorithm

Input: Sensor data up to current time t: $data_{1:t}$
Input: Abstract Indoor Floor Plan: fp
Input: Hidden State Sequence and Its Length up to last time $t-1$: $S_k(t-1)$, k
Input: Array of Viterbi variable and backward pointer: $VtbArr_k(t-1)$
Output: Pedestrian's position estimation at current time t: $Ped_{loc}(t)$
Output: Optimal state sequence estimation at current time t: $Q(t)$

$Ped_{AT}(t), at \leftarrow activity\_detect(data_{1:t})$
if $Ped_{AT}(t)$!= $None$ **then**
  $st \leftarrow at$
  // Calculate the transition probability
  $S(t) \leftarrow [\,]$
  for $s_i \in S_k(t-1)$ **do**
    // Select next segments according to fp
    $S^i(t) \leftarrow next(fp, s_i)$
    // Extract segments according to Wi-Fi data
    $S^{i,wifi}(t) \leftarrow extract(data^{wifi}_{st:t}, S^i(t))$

for $s_j \in S^{i,wifi}(t)$ **do**
$tr[i][j] \leftarrow p(s_j|s_i, Ped_{AT}(t))$
end for
$S(t).extend(S^{i,wifi}(t))$
end for
// Calculate the observation probability
$z_t \leftarrow dead\_reckon(data_{st:t})$
for $s_i \in S(t)$ **do**
$ob[i] \leftarrow p(z_t|s_i)$
end for
$VtbArr_{k+1}(t) \leftarrow viterbi(VtbArr_k(t-1), ob[\,], tr[\,][\,])$
$k \leftarrow k + 1$
$S_k(t) \leftarrow S(t)$
else// Not a location-related activity
$ob \leftarrow [\,],\ S_k(t) \leftarrow S_k(t-1)$
// Update the observation probability
$z_t = dead\_reckon(data_{st:t})$
for $s_i \in S_k(t)$ **do**
$ob[i] \leftarrow p(z_t|s_i)$
end for
$VtbArr_k(t) \leftarrow viterbi(VtbArr_k(t-1), ob[\,])$
end if
// Optimal State Sequence
$Q(t) \leftarrow None$
if $check\_status(VtbArr^k(t)) = Convergence$ **then**
$Q(t) \leftarrow viterbi\_decode(VtbArr^k(t))$
end if
// Update the location estimation according to $Q(t)$
$Ped_{loc}(t) \leftarrow update\_location(data_{st:t}, Q(t))$

5 Evaluation

5.1 Environment Setup

In this section, we show our evaluation for the performance of AiFiMatch in real-world environment, we conducted experiments in the fifth floor of a teaching hall on campus. Approximately, we covered a $78.95m \times 56.40m$ floor plan, as shown in Fig. 9a. A prototype is implemented and installed on a 360 N5 Android version 6.0.1 smartphone, a OPPO R827T Android version 4.4.0 smartphone and a Xiaomi 3W Android version 6.0.1 smartphone. The prototype samples the accelerometer, gyroscope and magnetometer sensors at 50Hz and Wi-Fi at 1Hz. Three participants (two males and one female) were asked to complete the experiments. The participants were asked to walking along Trajectory $No.1$ (T_1), Trajectory $No.2$ (T_2) and Trajectory $No.3$ (T_3) in a constant speed. Each trajectory was repeated six times by all participants. In order to record the walking trajectories, all the participants' shoes were painted with colored powder. This offered the ground truth.

5.2 Performance of Map Matching

To evaluate AiFiMatch map matching performance, we start by showing the online positioning performance of AiFiMatch and basic PDR technique. After that, we analyze the effect of step length and heading errors on positioning accuracy. Then, we discuss the convergence performance as compared to an activity sequence-based map matching algorithm proposed by *Zhou et al* [8]. Finally, we show the offline positioning results when using AiFiMatch.

Online Positioning Performance: Euclidean distance between the estimated position and the ground truth is introduced to indicate positioning accuracy. Fig. 6 shows the online positioning results of all trajectories for basic PDR algorithm with known initial point and AiFiMatch without known initial point. Here, the mean position of all segment candidates' starting point is taken as initial point of AiFiMatch algorithm. Generally, for one trajectory, the greater the traveled distance, the larger the positioning error of PDR due to cumulative errors, Fig. 6 shows the trend. However, after passing a number of steps, the traveled segment sequence determined by AiFiMatch even without known the initial point and the cumulative errors are eliminated successfully.

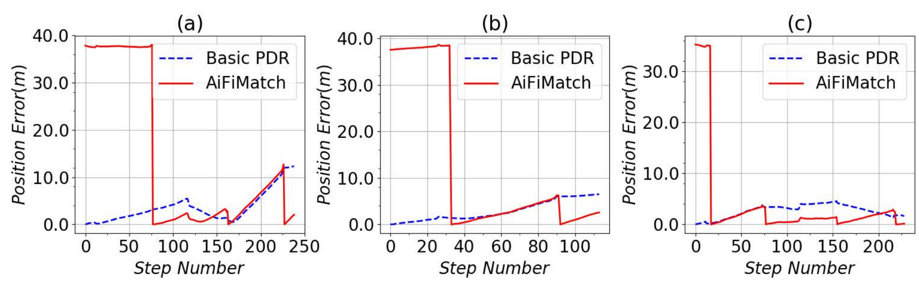


Fig. 6. Online Positioning Results for Each Trajectory. (a) T_1. (b) T_2. (c) T_3

Influence of Step Length and Heading direction Errors: The major errors of PDR techniques are mainly from step length and heading direction errors. Therefore, we analyze the influence of step length and heading direction errors to the average online positioning errors. Both of them are supposed to follow the Gaussian distributions with a mean zero. σ_s denotes the standard deviation of step length estimation and σ_φ denotes the standard deviation of heading direction estimation. When σ_s changes from 0.1 m to 0.5 m, σ_φ is set to 10 degree. When σ_φ changes from 10 degree to 50 degree, σ_s is set to 0.1 m. Fig. 7 shows the results of all trajectories with different errors. The performance of AiFiMatch in all error cases is superior to the basic PDR technique. From Fig. 7 *(a)-(c)*, with increasing step length error, the average online positioning errors increases gradually. The same trend is shown in Fig. 7 *(d)-(f)*, reflecting the influence of heading direction errors on the average online positioning errors. T_1 and T_3 have five location-related activities while T_2 has only two. As a result, given the same heading direction errors, the online positioning performance of AiFiMatch is more robust to T_1 and T_3 than T_2, which can also be seen from Fig. 7 *(d)-(f)*.

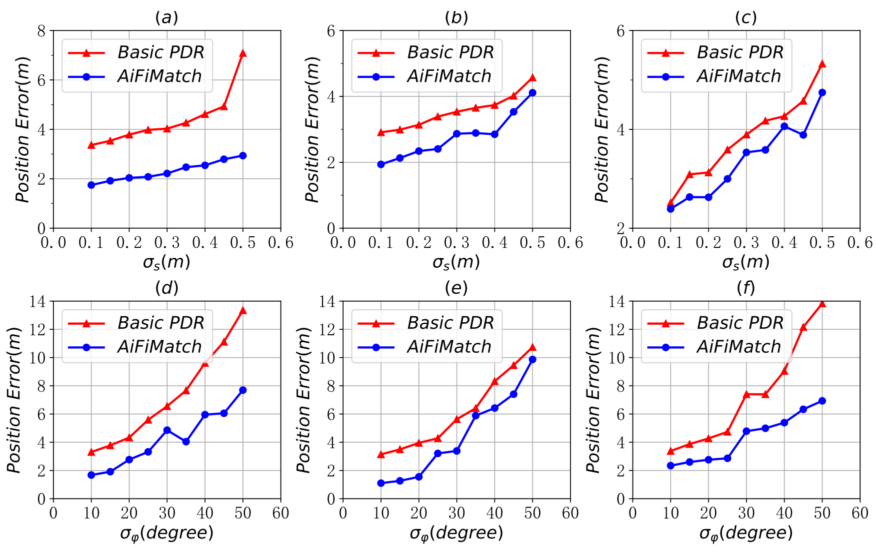


Fig. 7. Online Positioning Errors for Each Trajectory with Given Standard Deviations of Step Length and Heading Direction. (a) T_1. (b) T_2. (c) T_3. (d) T_1. (e) T_2. (f) T_3.

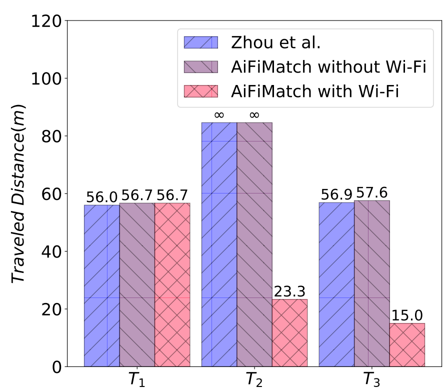
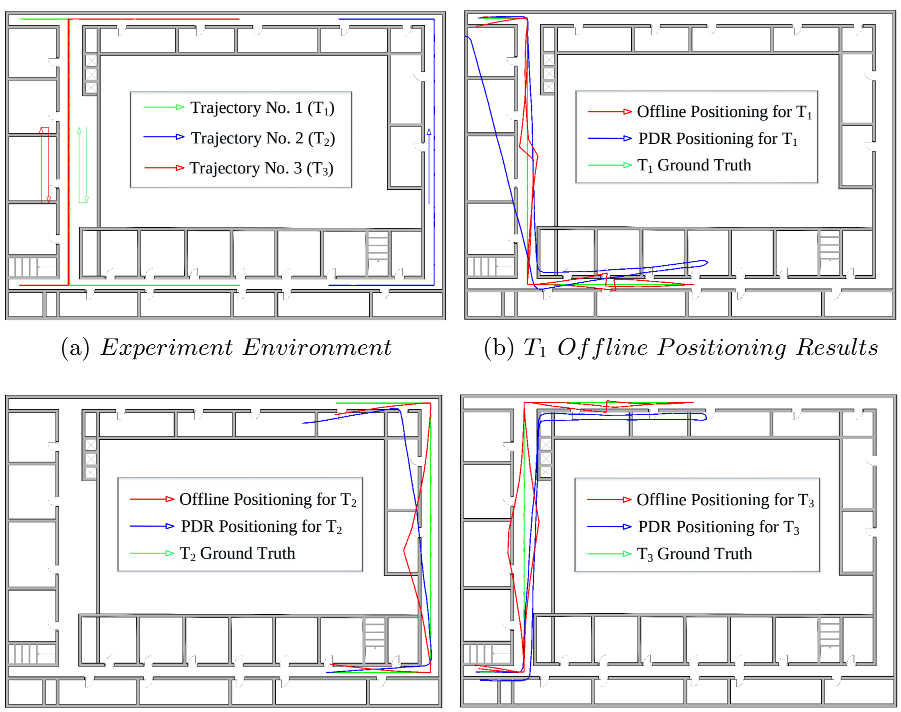


Fig. 8. Distance traveled before convergence for each trajectory.

Convergence Speed: We compare the performance of AiFiMatch algorithm in terms of convergence to map matching algorithm proposed by *Zhou et al.*

Distance traveled before converging to a unique states sequence reflects the convergence speed. The greater the traveled distance, the slower is the convergence speed. Fig. 8 shows the traveled distance before convergence for *Zhou et al*, AiFiMatch without Wi-Fi enhancement and AiFiMatch with Wi-Fi enhancement. At the initial stage, fingerprint database is empty (T_1), AiFiMatch and *Zhou et al.* both successfully converge even without known the initial point. AiFiMatch without Wi-Fi enhancement and map matching algorithm proposed by *Zhou et al.* fail to converge (∞ means T_2 cannot be converged.) due to the symmetry of building structure. However, with the help of Wi-Fi signal, T_2 reaches convergence quickly. Mostly, with Wi-Fi enhancement, the traveled distance is much shorter than without Wi-Fi enhancement(T_2, T_3).

Offline Positioning Performance: The offline positioning results are derived retrospectively after matching the walking trajectory of a pedestrian to a unique road segments sequence by AiFiMatch. Fig. 9 shows the tracking trajectories and some details are summarized in Table 2. AiFiMatch system tracked pedestrians' trajectories accurately in the experiment environments and the mean error of the offline positioning is about 1.24 m.



(a) *Experiment Environment* (b) T_1 *Offline Positioning Results*

(c) T_2 *Offline Positioning Results* (d) T_3 *Offline Positioning Results*

Fig. 9. Environment setup and offline positioning results for each trajectory

Table 2. Evaluation Results

Trajectory No.	Length (m)	Mean Error (m)	Step Number	Detected Step	Activity Number	Detected Activity
1	176.1	1.09	238	**240**	5	5
2	84.6	1.65	114	114	3	3
3	175.9	1.19	228	**227**	5	5

6 Conclusion

This paper proposed AiFiMatch: a novel map matching Algorithm based on activity detection and crowd-sourced Wi-Fi for indoor pedestrian tracking and positioning. AiFiMatch leverages the smartphone's motion sensors to detect different activities using a decision tree and then divides the walking trajectory into trajectory subset sequence. The HMM model is used to match walking trajectory subset sequence to road segments sequence. AiFiMatch can also construct and update fingerprint database based on road segment by crowd-sourcing. We provided the AiFiMatch's system architecture and presented the details of different modules. The performance of AiFiMatch has been evaluated by experiments in a building on campus. The results show that AiFiMatch can track pedestrian's trajectory accurately even without known initial point and is robust to a certain degree of step length and heading direction errors. In addition, with the help of Wi-Fi fingerprints, AiFiMatch reaches converge quickly and effectively solves the multiple hypotheses caused by symmetry of building structure.

References

1. Francisco Zampella, Antonio Ramón Jiménez Ruiz, and Fernando Seco Granja. Indoor positioning using efficient map matching, rss measurements, and an improved motion model. *IEEE Transactions on Vehicular Technology*, 64(4):1304–1317, 2015.
2. Paramvir Bahl, Venkata N Padmanabhan, and Anand Balachandran. Enhancements to the radar user location and tracking system. *Microsoft Research*, 2(MSR-TR-2000-12):775–784, 2000.
3. Robert J Fontana and Steven J Gunderson. Ultra-wideband precision asset location system. In *2002 IEEE Conference on Ultra Wideband Systems and Technologies - Digest of Papers*, pages 147–150. IEEE, 2002.
4. Lionel M Ni, Yunhao Liu, Yiu Cho Lau, and Abhishek P Patil. Landmarc: indoor location sensing using active rfid. *Wireless networks*, 10(6):701–710, 2004.
5. Faheem Zafari and Ioannis Papapanagiotou. Enhancing ibeacon based micro-location with particle filtering. In *Global Communications Conference (GLOBECOM)*, pages 1–7. IEEE, 2015.
6. Ningjia Fu, Jianzhong Zhang, Wenping Yu, and Changhai Wang. Crowdsourcing-based wifi fingerprint update for indoor localization. In *Proceedings of the ACM Turing 50th Celebration Conference-China*, page 34. ACM, 2017.

7. F Taia Alaoui, Valerie Renaudin, and David Betaille. Points of interest detection for map-aided pdr in combined outdoor-indoor spaces. In *2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, pages 1–8. IEEE, 2017.
8. Baoding Zhou, Qingquan Li, Qingzhou Mao, Wei Tu, and Xing Zhang. Activity sequence-based indoor pedestrian localization using smartphones. *IEEE Transactions on Human-Machine Systems*, 45(5):562–574, 2015.
9. Heba Aly and Moustafa Youssef. semmatch: Road semantics-based accurate map matching for challenging positioning data. In *Proceedings of the 23rd SIGSPATIAL International Conference on Advances in Geographic Information Systems*, page 5. ACM, 2015.
10. Baoding Zhou, Qingquan Li, Qingzhou Mao, Wei Tu, Xing Zhang, and Long Chen. Alimc: Activity landmark-based indoor mapping via crowdsourcing. *IEEE Transactions on Intelligent Transportation Systems*, 16(5):2774–2785, 2015.
11. Heba Abdelnasser, Reham Mohamed, Ahmed Elgohary, Moustafa Farid Alzantot, He Wang, Souvik Sen, Romit Roy Choudhury, and Moustafa Youssef. Semanticslam: Using environment landmarks for unsupervised indoor localization. *IEEE Transactions on Mobile Computing*, 15(7):1770–1782, 2016.
12. Chen Qiu and Matt W Mutka. iframe: Dynamic indoor map construction through automatic mobile sensing. *Pervasive and Mobile Computing*, 38:346–362, 2017.
13. Bang Wang, Qiuyun Chen, Laurence T Yang, and Han-Chieh Chao. Indoor smartphone localization via fingerprint crowdsourcing: Challenges and approaches. *IEEE Wireless Communications*, 23(3):82–89, 2016.
14. Xinglin Zhang, Zheng Yang, Chenshu Wu, Wei Sun, Yunhao Liu, and Kai Xing. Robust trajectory estimation for crowdsourcing-based mobile applications. *IEEE Transactions on Parallel and Distributed Systems*, 25(7):1876–1885, 2014.
15. Liyao Xiang, Tzu-Yin Tai, Baochun Li, and Bo Li. *tack* : learning towards contextual and ephemeral indoor localization with crowdsourcing. *IEEE Journal on Selected Areas in Communications*, 35(4):863–879, 2017.
16. Paul Newson and John Krumm. Hidden markov map matching through noise and sparseness. In *Proceedings of the 17th ACM SIGSPATIAL international conference on advances in geographic information systems*, pages 336–343. ACM, 2009.
17. Jochen Seitz, Jasper Jahn, Javier Gutiérrez Boronat, et al. A hidden markov model for urban navigation based on fingerprinting and pedestrian dead reckoning. In *2010 13th Conference on Information Fusion (FUSION)*, pages 1–8. IEEE, 2010.
18. Oliver Woodman and Robert Harle. Pedestrian localisation for indoor environments. In *Proceedings of the 10th international conference on Ubiquitous computing*, pages 114–123. ACM, 2008.
19. Haitao Bao and Wai-Choong Wong. An indoor dead-reckoning algorithm with map matching. In *2013 9th International Wireless Communications and Mobile Computing Conference (IWCMC)*, pages 1534–1539. IEEE, 2013.
20. Anshul Rai, Krishna Kant Chintalapudi, Venkata N Padmanabhan, and Rijurekha Sen. Zee: Zero-effort crowdsourcing for indoor localization. In *Proceedings of the 18th annual international conference on Mobile computing and networking*, pages 293–304. ACM, 2012.
21. Zhuoling Xiao, Hongkai Wen, Andrew Markham, and Niki Trigoni. Lightweight map matching for indoor localisation using conditional random fields. In *Proceedings of the 13th international symposium on Information processing in sensor networks*, pages 131–142. IEEE Press, 2014.

22. Dmytro Bobkov, Ferdinand Grimm, Eckehard Steinbach, Sebastian Hilsenbeck, and Georg Schroth. Activity recognition on handheld devices for pedestrian indoor navigation. In *2015 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, pages 1–10. IEEE, 2015.
23. Sheng Guo, Hanjiang Xiong, Xianwei Zheng, and Yan Zhou. Activity recognition and semantic description for indoor mobile localization. *Sensors*, 17(3):649, 2017.
24. Brian Ferris, Dieter Fox, and Neil Lawrence. Wifi-slam using gaussian process latent variable models. In *International Joint Conference on Artifical Intelligence*, pages 2480–2485, 2007.
25. Manh Kha Hoang, Joerg Schmalenstroeer, Christian Drueke, et al. A hidden markov model for indoor user tracking based on wifi fingerprinting and step detection. In *2013 Proceedings of the 21st European Signal Processing Conference (EUSIPCO)*, pages 1–5. IEEE, 2013.
26. Valentin Radu and Mahesh K Marina. Himloc: Indoor smartphone localization via activity aware pedestrian dead reckoning with selective crowdsourced wifi fingerprinting. In *2013 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, pages 1–10. IEEE, 2013.
27. He Wang, Souvik Sen, Ahmed Elgohary, Moustafa Farid, Moustafa Youssef, and Romit Roy Choudhury. No need to war-drive: Unsupervised indoor localization. In *Proceedings of the 10th international conference on Mobile systems, applications, and services*, pages 197–210. ACM, 2012.
28. Julien Bloit and Xavier Rodet. Short-time viterbi for online hmm decoding: Evaluation on a real-time phone recognition task. In *ICASSP*, pages 2121–2124. IEEE, 2008.