Indoor Positioning using Similarity-based Sequence and Dead Reckoning without Training

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Abstract—For the traditional fingerprinting-based positioning approach, it is essential to collect measurements at known locations as reference fingerprints during a training phase, which can be time-consuming and labor-intensive. This paper proposes a novel approach to track a user in an indoor environment by integrating similarity-based sequence and dead reckoning. In particular, we represent the fingerprinting map as location sequences based on distance ranking of the APs (access points) whose positions are known. The fingerprint used for online positioning is represented by a ranked sequence of APs based on the measured Received Signal Strength (RSS), which is referred to as RSS sequence in this paper. Embedded into a particle filter, we achieve the tracking of a mobile user by fusing the sequence-based similarity and dead reckoning. Extensive experiments are conducted to evaluate the proposed approach.

Index Terms—indoor positioning, similarity-based sequence, particle filtering, dead reckoning.

I. INTRODUCTION

Research community has shown an increasing interest in indoor positioning due to the rapid demand of location-based services [1]. In the literature, various techniques including Received signal strength (RSS) [2], time-of-arrival (TOA) [3], and angle-of-arrival (AOA) [4] have been used for positioning. A number of propagation model-based or fingerprinting-based techniques have been proposed [5].

Propagation model-based approach [6] needs a model to explicitly characterize the propagation of radio signals. Its accuracy is limited due to multipath issues of radio signal propagation in indoor environments. On the contrary, fingerprinting-based approach [7] represents locations using a priori sets of sensor measurements collected during an offline training phase. The location of a user is then determined by matching current measurement with reference fingerprints. These approaches are shown to have better accuracy as compared to the model-based approaches.

A good positioning accuracy is guaranteed by a time-consuming and thorough site survey phase which collects the radio measurements at reference locations through the environment. Although different techniques [3] [9] are proposed to reduce this phase, maintaining the fingerprinting map is still labor-intensive due to the change of the environment.

To overcome the tedious site survey phase to construct the fingerprinting map, we use the sequence-based approach, which is based on our previous work in [10] [11]. The technique is also used by other researchers [12] [13] to localize and track mobile users. In particular, the sequence-based fingerprinting map consists of a set of connecting regions, which is represented by a ranked sequence (i.e., location sequence) based on the distance to the APs. Fig. 1(a) shows one example of the fingerprinting map. In the online localization and tracking phase, the RSS sequence is formulated by ranking the measured RSS of the APs in descending order. The location of a user can be simply determined by those location sequences whose similarities best match the RSS sequence [10].

Due to multipath effect on radio signal propagation, it is common that the measured RSS sequence does not match the true location sequence, thus resulting in a poor positioning accuracy. Due to cost-effective feature, modern smart phones are equipped with IMU (inertial measurement unit) sensors. These sensors can be used to implement a dead reckoning which can precisely track the position of a user for short period of time. However, the error is accumulated for long term run, which must be corrected by other sources of sensors. Therefore, we propose a novel method to track a user by fusing similarity-based sequence and dead reckoning using a particle filter. The proposed approach can incorporate the measurements from various sources of sensors (e.g., Wifi and IMU) with complementary error characteristics to improve the positioning accuracy. Moreover, our approach does not require the tedious training phase to construct the fingerprinting map, as compared to the traditional fingerprinting-based approach.

We highlight the contributions of this paper as follows:

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We propose to fuse similarity-based sequence based on relative signal strength for the tracking of mobile users without the need for training.

We design a particle filtering that fuses Wifi and IMU measurements to achieve a better tracking accuracy.

We implemented our approach and evaluated its performance through extensive experiments. Note that the whole implementation is using a smartphone only, without any external device.

We organize the rest of this paper as follows. We present the system overview in Sect. II, which is followed by the details of the particle filtering in Sect. III. We show the experimental details in Sect. IV and conclude this paper in Sect. V.

II. SYSTEM OVERVIEW

This paper proposes a novel approach to combine similarity-based sequence and dead reckoning to localize and track users without the need of training. To be precise, we use a sequence-based technique to construct the fingerprinting map without human intervention. As illustrated in Fig. 2, our proposed system consists of two phases, namely: 1) an offline phase to construct the reference fingerprinting map and 2) an online phase to localize and track mobile users.

A. Offline Construction of Reference Fingerprinting Map

In this phase, the reference fingerprinting map is constructed by partitioning the environment into a set of regions. Each region is associated with a location sequence, which is represented as the ranking of APs based on their distance in ascending order. This phase results in a set $\mathbf{m} = \{ (f_1, \mathbf{l}_1), ..., (f_M, \mathbf{l}_M) \}$ of $M$ fingerprints, where $f_i$ is the location sequence and $\mathbf{l}_i = (x_i, y_i)$ is the 2D location.

An example of the fingerprinting map constructed with four APs is shown in Fig. 1(a), where $\mathbf{f}$ denotes the location of the $k$th access point. We show an example to compute the location sequence at a position in Fig 1(b). In this example, the order of reference APs is predefined as $1234$. Ranking the APs in ascending order based on their distances away from $A$, we will get the location sequence at location $A: \mathbf{f} = 3421$.

B. Online Localization and Tracking

In the online phase, we measure the RSS from APs and formulate them as the RSS sequence by ranking the APs based on the strength in descending order. Fig. 3(b) shows an example to compute the RSS sequence at $t = 30$ s.

In theory, the measured RSS sequence should fully match the location sequence of the region where the user locates. In practice, radio signal propagation suffers from multi-path effect mainly due to reflection surfaces in the environment. Therefore, it is not surprised that the measured RSS sequence is not identical to the true location sequence. For example, Fig. 3(a) shows the signal strength from four access points at location $A$ in Fig. 1 for a duration of 40 seconds. The true location sequence at this location is $3421$, while the measured RSS sequence is $g_t = 2341$ at $t = 30$ s (see Fig. 3 in detail).

The measured RSS sequence $g_t$ is then matched against the location sequence $f_t$ in the fingerprinting map $\mathbf{m}$ to compute the similarity-based sensor model for the correction of particle filtering (see Sect. III-A). We further integrate step counting and orientation information from IMU into a particle filter to track a mobile user. An overview of the online localization and tracking using a particle filter with similarity comparison is shown in Fig. 4 and will be described in the next section.

III. PARTICLE FILTERING WITH SIMILARITY COMPARISON

A. Particle Filtering

We consider the estimation of the pose of user $x_t$ at time $t$ as Bayesian inference. Formally, we denote $g_{1:t}$ as the WiFi measurements until time $t$, $u_{1:t}$ as the dead reckoning input from IMU sensor, and $\mathbf{m}$ as the reference fingerprinting map. The goal is to estimate the posterior probability $p(x_t | g_{1:t}, u_{1:t})$. Based on Bayesian inference, we can further factorize $p(x_t | g_{1:t}, u_{1:t})$ into:

$$p(x_t | g_{1:t}, u_{1:t}, m) = \eta_k \cdot p(x_t | x_{t-1}, u_t) \cdot p(g_t | x_t, m) \cdot p(x_{t-1} | g_{1:t-1}, u_{1:t-1}, m),$$

(1)

where $\eta_k$ is a normalizer to ensure that the sum of total probability equals to one. $p(x_t | x_{t-1}, u_t)$ is the motion model, which predicts the pose of a user at time $t$ based on the previous pose $x_{t-1}$ and dead reckoning from IMU $u_t$. $p(g_t | x_t, m)$ is the observation model, which represents the likelihood of receiving a measurement $g_t$ at pose $x_t$ given the reference fingerprinting map $\mathbf{m}$ (see Sect. III-B). We choose the particle filter as an implementation due to its non-parametric feature.

For the particle filtering, the pose of a user $x_t$ is represented by a set of particles $x_t = \{ x_t^{[i]}, u_t^{[i]} \}_{i=1}^N$, where $N$ is the number of particles. Each particle consists of pose hypotheses $x_t^{[i]} = \{ x_t^{[i]}, y_t^{[i]}, \theta_t^{[i]} \}$ (i.e., 2D position $\{ x_t^{[i]}, y_t^{[i]} \}$ and orientation $\theta_t^{[i]}$) and the weight $w_t^{[i]}$. In general, the
neighbors (WKNN) approach. Based on a similarity measure [14], we approximate the location sequence map \( m \). Observation Model based on Sequence Similarity generates a set of new particles as a replacement of the old set of particles based on their weights.

B. Observation Model based on Sequence Similarity

The observation model \( p(g_t|x_t,m) \) represents the likelihood of receiving a measurement \( g_t \) at pose \( x_t \) given the location sequence map \( m = \{ (f_1, \ell_1), \ldots, (f_M, \ell_M) \} \). Similar to [13], we approximate \( p(g_t|x_t,m) \) using weighted k-nearest neighbors (WKNN) approach. Based on a similarity measure \( \text{sim}(g_t, f_i) \), we could obtain the \( k \) reference fingerprints \( f_{\pi(1)}, \ldots, f_{\pi(k)} \) whose similarities best match the measured RSS sequence \( g_t \). Then \( p(g_t|x_t,m) \) is approximated as:

\[
p(g_t|x_t,m) \approx \sum_{j=1}^{k} \text{sim}(g_t, f_{\pi(j)}) \exp\left(-\frac{1}{2}d^2(x_t, \ell_{\pi(j)})\right),
\]

where \( d^2(\cdot) \) is a squared distance measure to assess the translational displacement.

\[
d^2(x_t, \ell_{\pi(j)}) = \frac{(x_t - x_{\pi(j)})^2}{\lambda} + \frac{(y_t - y_{\pi(j)})^2}{\lambda},
\]

where \( \lambda \) is parameter to control the bandwidth of the translational displacement. The impact of parameter \( \lambda \) on the tracking accuracy is shown in Sect. IV-C.

We use Kendall Tau coefficient to compute the similarity \( \text{sim}(g_t, f_i) \) between the measured RSS sequence \( g_t \) and location sequence \( f_i \):

\[
\tau(g_t, f_i) = \frac{n_c(g_t, f_i) - n_d(g_t, f_i)}{\frac{1}{2}n(n-1)},
\]

where \( n_c(g_t, f_i) \) and \( n_d(g_t, f_i) \) are the numbers of concordant pairs and discordant pairs between \( g_t \) and \( f_i \) respectively and \( n \) is the length of \( g_t \) and \( f_i \). As a requirement, the similarity usually lies in 0 and 1, therefore \( \text{sim}(g_t, f_i) = \frac{1+\tau}{2} \).

C. Fuse Dead Reckoning Information from Phone IMU

We utilize the IMU sensor inside the phone to achieve dead reckoning. The IMU consists of a 3D accelerometer, a 3D gyroscope, and a 3D magnetometer. We implemented the auto-correlation based step counting in [9]. Given the accelerometer data, [9] achieved step counting by discovering the periodic step patterns through normalized auto-correlation. The magnetometer reading from the IMU is used as the orientation of the user by assuming the phone is always held by a person in front of him during walking.

As a result, the phone will send the current step counting \( c_t \) and the orientation \( \theta_t \) (i.e., \( u_t = (c_t, \theta_t) \)) to the server for the sensor fusion (see Fig. 2). The state of a particle is predicted based on the dead reckoning corrupted with a Gaussian noise:

\[
x_t = x_{t-1} + s \cdot (c_t - c_{t-1}) \cdot \cos(\theta_{t-1}) \cdot (1 + \mathcal{N}(0, \sigma_d^2)) \quad (5)
\]

\[
y_t = y_{t-1} + s \cdot (c_t - c_{t-1}) \cdot \sin(\theta_{t-1}) \cdot (1 + \mathcal{N}(0, \sigma_d^2)) \quad (6)
\]

\[
\theta_t = \theta_{t-1} + (\alpha_t - \alpha_{t-1}) \cdot (1 + \mathcal{N}(0, \sigma_\theta^2)), \quad (7)
\]

where \( s \) is the step length, \( \sigma_d \) and \( \sigma_\theta \) are Gaussian noises added to distance displacement and orientation respectively.

IV. EXPERIMENTAL RESULTS

A. Experimental Setsup

We evaluated our approach in an office environment with a size of 25 m x 14 m, as shown in Fig. 4(a). This environment consists of concrete walls, soft room partitions, furniture, and equipments. Nine access points (ASUS RT-N12HP) are installed with known positions. The phone processes the IMU data with a frequency of 50 Hz and sends the computed results \( u_t \) to a server once a step is detected. A Sony Z2 phone is used to retrieve the signal strength from the APs and upload them to the server with a frequency of 0.5 Hz.

During our experiment, a user held a mobile phone (see Fig. 4(b)) and walked along a rectangle path multiple times with a normal speed. In total, he traveled approx. 648.2 meters in 831 seconds with an average velocity of 0.8 m/s. This resulted in a track consists of 415 Wifi and IMU measurements. To record the ground truth, we placed 302 visual landmarks on the walls. When the user passed by the landmarks, he is asked to press a button on the phone to send the ID of the landmark to the server. The positions of these landmarks are measured before. A snapshot of the experiment is shown in Fig. 4(b).

To compare to the traditional fingerprinting-based approach, we recorded the Wifi measurements manually at 41 locations as reference fingerprints as shown in Fig. 4(a). The locations of these positions are known before hand. At each reference position, we recorded Wifi measurements for 3 minutes. We implemented a traditional fingerprinting-based approach based on the cosine similarity [15] and WKNN for a comparison.

We use a grid-based representation to compute our sequence-based fingerprinting map. We discretize the environment into two-dimensional grids with a fixed grid size. The location sequence in each grid is represented by the ranking of distance from the centroid of this grid to APs. We performed various experiments to evaluate the performance our approach.

B. Tracking Performance With and Without Integrating IMU

We first examined the tracking accuracy with and without incorporating IMU. We set the noise scale \( \sigma_d = 0.4 \) and \( \sigma_\theta =
choose the number of particles are shown in Fig. 5(c). It can be seen from this figure, the large or too small noise scale obviously gives a bad result. For example, we obtained a mean tracking accuracy of 2.67 m by integrating IMU, which leads to an improvement of 48.8%, as compared to the result without IMU (5.22 m). This is because IMU is precise to measure the change of position over short periods of time, therefore can be used to improve the overall tracking accuracy. With IMU alone, the track will drift due to the accumulative characteristics. For example, the mean tracking error of IMU alone is 27.5 m, while our approach achieves an accuracy of 2.67 m.

We evaluated the tracking accuracy under the impact of different noise scales (σ_d and σ_θ) added to the IMU. We choose the number of particles N = 1000 and the results are shown in Fig. 5(c). It can be seen from this figure, the best setting of parameters is σ_d = 0.4 and σ_θ = 0.01. A too large or too small noise scale obviously gives a bad result.

C. Impact of Different Number of Particles

We examined the tracking accuracy under different number of particles N, as shown in Fig. 6(a). As can be seen from this figure, the tracking accuracy gets worse with smaller N (e.g., N ≤ 100). With N ≥ 1000, we achieved nearly the same tracking accuracy. Obviously, the mean computational time required for larger N increases due to the increasing number of particles. Our experiments show that integrating one measurement with N = 1000 on an Intel Core i5-4200M@2.50 GHz CPU with 4 GB RAM only requires 6.02 ms, which satisfies the requirement of real-time processing. We also show the impact of λ on the tracking performance in Fig. 6(a). Our experiments revealed that λ = 0.01 is the best choice for all settings of N. A too larger or too smaller λ obviously leads to a poor result.

D. Impact of Different Step Length s

We examined the tracking accuracy under various step length s in Fig. 6(b). We also varied σ_d to see its impact on the tracking accuracy, due to its high impact on the tracking performance. As can be seen from Fig. 6(b), the tracking accuracy gets worse with a too large or too small step length. A choice of s = 0.7 gives the best tracking results. In addition, σ_d = 0.4 leads to the best tracking accuracy, which is consistent with the findings in Sect. V-B. The step length may be different for various persons, an algorithm to estimate the step length can be found in [16].

E. Compare to Traditional Fingerprinting-based Approach

Finally, we compared our approach with a state-of-the-art fingerprinting-based approach using cosine similarity and WKNN [15]. IMU information is integrated for both approaches with a noise setting of σ_d = 0.4 and σ_θ = 0.01. We fix λ = 0.01 and N = 1000. We choose different values of k and various grid sizes of our approach to evaluate the tracking performance. The mean tracking accuracy is shown in Fig. 6(c). As can be seen from this figure, k = 4 gives the best results for the traditional fingerprinting-based approach and our proposed approach with a grid size of 2.0 m. For both approaches, a too larger k obviously leads to a worse result. The traditional fingerprinting-based approach achieves a tracking accuracy of 2.35 m with k = 4, which is slightly better than our sequence-based approach (with a mean tracking accuracy of 2.67 m). Fingerprinting-based approach requires a phase to collect the measurements as the reference fingerprinting, which can be very time consuming. In contrast, our approach eliminates this time-consuming phase, and achieves comparable results, therefore may be considered as a good alternative to other existing state-of-the-art fingerprinting-based approaches.

In addition, it can be seen from Fig. 6(c) that the optimal value of k varies for different grid sizes. To get a better accuracy, we need to assign a large k for a small grid size. For example, we achieve the best tracking accuracy with k = 4 for a grid size of 2.0, while the best setting for a grid size of 1.0 is k = 32. Moreover, the tracking accuracy gets slightly better with a smaller grid size. For example, the best accuracy achieved with a grid size of 1.0 is 2.55 m with k = 32, which is an improvement of 4% as compared with a grid size of 2.0 m (i.e., 2.67 m with k = 4).

F. Tracking Accuracy of Different Devices, Walking Speeds, and Sampling Rates

We evaluated the tracking accuracy under different devices and different walking speeds using our sequence-based approach. The same parameter setting in Sect. IV-C is applied for this series of experiments. We additionally recorded a track
and a low sampling rate obviously lead to bad results, since in both cases there are not enough WiFi measurements to correct the fingerprinting map, which is essential for the traditional fingerprinting-based approach. The tracking results are shown in Fig. 7. As can be seen from this figure, the two devices achieve similar tracking results (i.e., 2.67 m for Sony phone and 2.85 m for Samsung phone) with a normal walking speed. In addition, a fast walking speed and a low sampling rate obviously lead to bad results, since in both cases there are not enough WiFi measurements to correct the IMU drift thus leading to poor tracking results.

V. CONCLUSIONS

In this paper, we proposed a novel approach to combine similarity-based sequence technique and dead reckoning to localize and track users in indoor environments. Our approach does not require any tedious site survey phase to construct the fingerprinting map, which is essential for the traditional fingerprinting-based approaches. Extensive experiments were conducted to validate the performance of our approach. We achieved a mean tracking accuracy of 2.67 m, which is comparable to the traditional fingerprinting-based approach. For the future work, we would like to evaluate our approach in large scale environments. In addition, we want to investigate a novel similarity measure to improve the tracking performance.

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