

Real-time Smartphone Indoor Tracking Using Particle Filter with Ensemble Learning Methods

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Abstract—Location aware services in the Internet of Things are essential for smart environments. Location awareness enables operational systems to deliver useful information for supplying context-aware applications. We propose an efficient probabilistic model to provide good and stable localization accuracy in smart building environments for smartphones. Our proposed localization method fuses zone detection, radio-based ranging, inertial measurement units and floor plan information into an enhanced particle filter. Zone detection is designed with an ensemble learning algorithm by combining Hidden Markov Models and discriminative learning methods. We first apply ensemble learning models to achieve zone detection. Further, we integrate zone detection and an enhanced ranging model to achieve high and stable localization performance. Experiment results in an office-like indoor environment show that our system outperforms traditional localization approaches considering stability and accuracy. The localization method can achieve performance with an average localization error of 1.26 meters.

Keywords: Indoor Localization, Internet of Things, Particle Filter, Ensemble Learning Methods, Hidden Markov Model.

I. INTRODUCTION

Due to the growing ubiquitousness of the Internet of Things (IoT) and the importance of context aware services, indoor localization has become an important research topic. Several indoor localization methods (e.g. Wi-Fi-based fingerprinting, Wi-Fi or Bluetooth-based ranging, etc.) have been proposed. However, due to the ubiquitousness of Wi-Fi signals in indoor environments, Wi-Fi-based localization has become the dominant approach for indoor localization [4]. Wi-Fi received signal strength indicator (RSSI) is the most used parameter for indoor localization. It can be used both in range-based or fingerprinting-based approaches. The earth magnetic field (MF) in indoor environments presents distortions over space due to the presence of ferromagnetic materials, which can be also used to improve indoor localization accuracy [1].

We present an indoor localization approach by fusing zone detection, inertial measurement units (IMUs) and floor plan information in an enhanced particle filter. The zone detection method is designed using an ensemble learning algorithm by combining Hidden Markov Models (HMM) and discriminative learning methods. We define a zone as a subarea inside an area of interest. Further, we integrate zone detection results using an enhanced radio-based ranging model and floor plan information in a particle filter approach. Figure 1 presents an

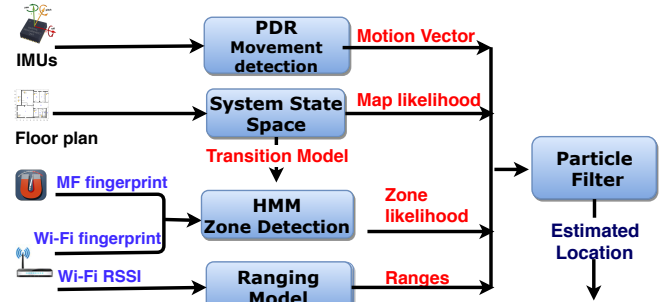


Figure 1: Indoor Localization System Architecture Overview.

architecture overview of our proposed approach. The main contributions of this work are as follows.

- We design an enhanced particle filter fusing the detected zone, radio-based ranges, IMUs and coarse-grained floor plan information to achieve accurate and stable indoor localization performance.
- We conduct a set of experiments to validate the performance of our localization method. We evaluate our system in a complex environment along three different moving paths. With an average localization error of 1.26 meters, our approach outperforms other traditional solutions in terms of stability and accuracy.

The rest of the paper is organized as follows. Section II presents related work. The localization approach is reviewed in Section III. Section IV presents the implementation details of the localization system. Section V describes the performance evaluation results. Section VI concludes the paper.

II. RELATED WORK

Pedestrian Dead Reckoning (PDR) has attracted research interest due to the fast development of IMUs in modern smartphones. IMUs can be leveraged to implement pedestrian movement detection such as heading orientation, step recognition, stride length estimation [12]. Thus, by using IMUs, PDR systems estimate the new location based on the previously determined location. For instance in [3], [8], the heading orientation is determined based on gyroscope measurements, whereas the displacement is estimated from accelerometer readings. PDR systems measure position changes rather than the absolute position, which results in an accumulation of sensor errors over time.

Radio signals are often used to provide indoor localization. In [15] for instance, the authors propose to use received signal strength indicator (RSSI), whereas in [11] time information related to radio propagation is applied. Radio-based indoor localization can be classified as range-based and range-free methods. The first stage in range-based localization methods is to calculate the propagation distances, which is called ranging. Then, different positioning algorithms can be used to estimate the absolute locations of the targets, such as trilateration [10]. In range-free localization methods, fingerprinting [2] is very often used because of its robustness to multi-path propagation. However, it is very time consuming to build up a radio map, which is required to locate the targets in fingerprinting. Typically, ranging requires much less labor efforts than building a radio map for fingerprinting.

III. SYSTEM OVERVIEW

Figure 1 summarizes the architecture of our proposed approach, which includes four key subcomponents: an ensemble learning method for zone prediction, an enhanced ranging method, a PDR-based movement detection method and an enhanced particle filter. Additionally, the floor plan information defines the system state, the map likelihood (i.e., allowed areas to spread particles), and the transition model (i.e., connections among zones).

A. Ensemble Learning Method for Zone Detection

The proposed ensemble learning method is based on the concept of Markov localization [7], which can be described by estimating the state of HMM with controllable state transitions. For the localization problem, we refer to zones as states of the HMM. Thus, our HMM is specified by the following components:

- A set of n states $Z = \{z_1, z_2, \dots, z_n\}$, where z_i is the identifier value of the zone i .
- A transition probability matrix A ,

$$A = a_{1,1}, a_{1,2}, \dots, a_{n,1}, \dots, a_{n,n}$$

where a_{ij} represents the probability of moving from zone z_i to zone z_j .

- A set of observations O ,

$$O = \{(o_1, o_2, \dots, o_m)_1, \dots, (o_1, o_2, \dots, o_m)_r\}, \quad (1)$$

where o_i is the zone prediction result of the i -th individual machine learning method.

- An emission probability matrix B ,

$$B = b_{1,1}, b_{1,2}, \dots, b_{1,r}, \dots, b_{n,r}$$

where $b_{i,j}$ represents the probability of an observation $(o_1, o_2, \dots, o_m)_j$ being generated at zone z_i .

- An initial probability distribution $\pi = \pi_1, \pi_2, \dots, \pi_n$ over zones.

Hereafter, we will refer to our HMM-discriminative learning model as HMM-d model. Given a sequence of observations $q_{t-i}, \dots, q_{t-1}, q_t$, and a settle model HMM $\lambda = \{\pi, A, B\}$, the sequence of hidden states $s_{t-i}, \dots, s_{t-1}, s_t$ can be estimated by employing the Viterbi algorithm [6].

B. Enhanced Particle Filter with Data Fusion

The aim of the positioning problem is to obtain the belief of the system state based on the observations, (i.e., posterior probability distribution). This posterior probability can be represented as a set of weighted particles. Thus, the current state of the system is determined by the probabilities of the particles. Particle filters estimate the posterior probability distribution of the system state based on some conditioned measurements q_t at time t [4]. At time t , the system state vector X_t is defined as follows:

$$X_t = [x_t, y_t, \theta_t, \ell_t, s_t], \quad (2)$$

where (x_t, y_t) are the Cartesian coordinates of the target object, θ_t is the heading orientation, ℓ_t is the stride length and s_t is the zone in which the target is located. The set of N weighted particles can be defined as:

$$P_t = [X_t^i, W_t^i], i = 1, \dots, N, \quad (3)$$

where X_t^i is the state vector and W_t^i is the associated weight of the i -th particle at time t . Measurements observed at time t can be modeled according to a non-linear function H as follows:

$$q_t = H(X_t) + u_t \quad (4)$$

where u_t is the noise included in the measurements at time t .

The associated weights can be calculated as follows:

$$w_t^i \propto w_{t-1}^i * p(q_t | X_t^i), \quad (5)$$

where $p(q_t | X_t^i)$ is the *likelihood* function calculated from the observation measurements vector at time t .

1) *Prediction Model*: Each location belongs to a zone s_t . Thus, the particle filter prediction function can be written as

$$X_t = [x_{t-1} + \ell_t \cdot \cos(\theta_t) y_{t-1} + \ell_t \cdot \sin(\theta_t), \theta_t, \ell_t, s_t], \quad (6)$$

Both θ_t and ℓ_t values are calculated by PDR methods [5] whereas s_t is a discrete random variable that identifies the zone where the particle is located at time t .

2) *Observation Model*: The associated weight update is based on the likelihood of the observations conditioned on each particle $P(q_t | X_t^i)$ at time t . The observation vector is defined by the estimated ranges to different ANs and the estimated zone information. Thus, the observation vector at time t is defined as $q_t = [\hat{d}_t, \hat{s}_t]$, where $\hat{d}_t$ contains ranges to different ANs and $\hat{s}_t$ is the observed zone.

Since the ranging method and the HMM-d method are completely independent, the range and zone prediction information are conditionally independent of each other. Therefore, the probability $P(q_t | X_t^i)$ can be determined as follows:

$$P(q_t | X_t^i) = P(d_t | X_t^i) \cdot P(s_t | X_t^i) \quad (7)$$

Hereafter, we refer to $P(q_t | X_t^i)$ as the overall likelihood, $P(d_t | X_t^i)$ as the ranging likelihood, and $P(s_t | X_t^i)$ as the zone likelihood. The particle at the absolute position (x_t, y_t) with low probability to observe d_t^j in their position will be

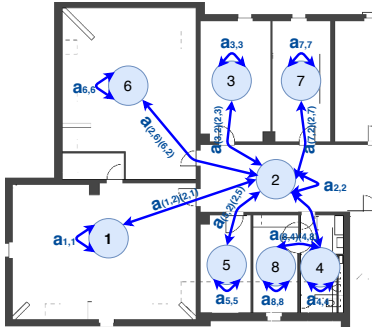


Figure 2: Zone definition and transition model for HMM-d.

assigned a small ranging likelihood. Particles positioned at different zones than the one observed by the HMM-d method will be assigned small zone likelihood values.

3) *Ranging likelihood*: Since ANs are programmed to operate independently, we can assume that the ranges to different ANs are independent from each other. Therefore, the ranging likelihood can be defined as follows:

$$P(d_t | X_t^i) = \prod_{j=1}^M P(\hat{d}_{j,t} | X_t^i), \quad (8)$$

where $\hat{d}_{j,t}$ is the measured distance to AN j at time t . $P(\hat{d}_{j,t} | X_t^i)$ is assumed to follow a normal distribution.

4) *Zone Likelihood*: Zone likelihood refers to the probability of observing the ground truth zone s_t in the current particle state X_t^i . Therefore, $P(s_t | X_t^i)$ can be written as:

$$P(s_t | X_t^i) = \frac{P(X_t^i | \hat{s}_t) \cdot P(\hat{s}_t)}{P(X_t^i)}, \quad (9)$$

where $\hat{s}_t$ is the observed zone at time t .

C. PDR-based Motion Vector Estimation

In order to estimate the pedestrian displacement, we use three smartphone embedded sensors: the accelerometer, gyroscope, and the geomagnetic field sensor. The displacement of the pedestrian at time t is defined by the motion vector $M_{v_t} = [\theta_t, \ell_t]$. The motion vector M_{v_t} is passed from the PDR component to the Particle Filter component at instant t when a step of the pedestrian is recognized in the target mobile object. Details about the motion vector estimation process can be found in our previous work [4].

D. Ranging Estimation Process

Some models relating RSSI to the propagation distance have been proposed e.g., Log Distance Path Loss (LDPL) [13], Nonlinear Regression Model (NLR) [10]. These models are called propagation models. In this work we use the NLR model. The NLR model is defined as Equation 10:

$$r = \alpha \cdot e^{(\beta \cdot Pw(r))}, \quad (10)$$

where both α and β are environmental variables.

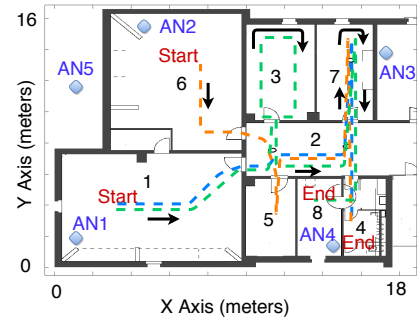


Figure 3: Zones, trajectories (dotted lines) and ANs distribution (Diamond blue points: Anchor Nodes)

IV. IMPLEMENTATION

We implemented a terminal-based system for real-time accurate indoor localization for smartphones. The system comprises two main components: a mobile target and a set of Wi-Fi Anchor Nodes (ANs). ANs are some commercial Wi-Fi access points. We have deployed the localization algorithms in a Motorola Nexus 6 smartphone (MT).

The system requires information related with zones' distribution and physical connections among zones (i.e., zone transition information). We define 8 zones, and each zone is a wall separated area (i.e., rooms, corridor). Figure 2 shows the zone distribution and the transition model. We selected and setup three different discriminative machine learning techniques (KStar, Multilayer Perceptron (MLP) and J48) for the zone prediction ensemble learning method HMM-d.

V. PERFORMANCE EVALUATION

Experiments were conducted in the building of the Institute of Computer Science at the University of Bern. A part of the third floor with an area of $288m^2$ ($18m \times 16m$) was chosen to deploy the localization system. The smartphone is held by a person moving along three different trajectories (Figure 3).

A. Room Level Localization Performance

In this section we consider the precision metric to evaluate our HMM-d model [9]. Precision can be expressed as $TP/(TP + FP)$. Where TP and FP are the true positive and false positive prediction rate respectively.

To compare our method to another ensemble learning model, we implemented a majority voting-based method, which is referred to as Voting method hereafter. The Voting method uses predicted zone labels from KStar, J48 and MLP for the majority voting rule [14].

As shown in Figure 4, HMM-d achieves more than 0.85% precision in all tested zones. However, in zones 3 and 4 HMM-d is outperformed by the KStar method. Therefore, HMM-d is able to predict the zone more reliably than the other tested learning methods. Our prediction model allows the production of better zone prediction performance compared to individual and ensemble voting models.

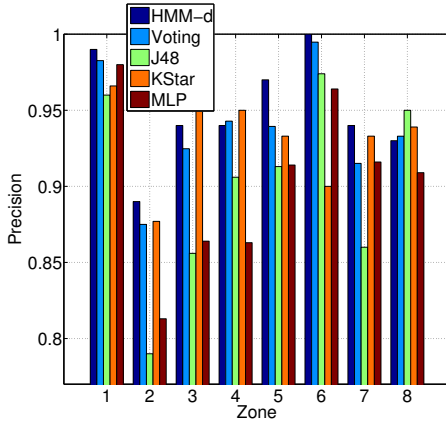


Figure 4: Zone Prediction Performance, Precision score.

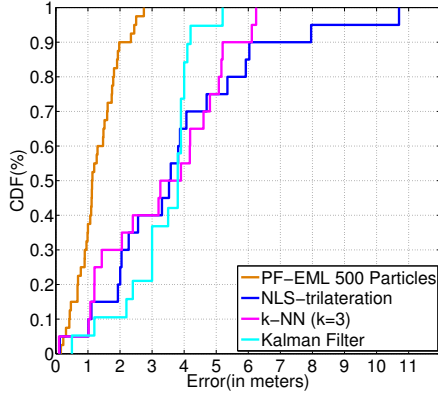


Figure 5: Localization error CDF of PF-ELM (500 particles), NLS, k-NN (k=3) and KF.

B. Indoor Tracking Accuracy

In this section we discuss the performance of the whole localization approach. Similar to other localization systems, we compare the performance of our method with the Non-linear Least Squares trilateration (NLST) algorithm, k-nearest neighbors (k-NN) fingerprinting and Kalman Filter-based (KF) localization methods.

Figure 5 depicts the CDF of localization errors for the best performance of PF-ELM, NLST and the k-NN method (k=3). Our localization approach outperforms NLST by around 75% and 66.56% regarding 90% accuracy and mean error respectively. Moreover, standard deviation of PF-ELM is 71.03% smaller than for NLST. k-NN ($k = 3$) localization achieves around 6.1m for 90% accuracy with a mean error of 3.32m and the standard deviation of 1.89m. The KF approach achieves around 4.1m for 90% accuracy, the mean error is 3.36m and the standard deviation is 1.11m. Thus, our localization approach outperforms k-NN by around 75%, and KF by around 51.2% regarding 90% accuracy. The mean error of the PF-ELM approach is 62.29% and 61.8% better than for KF and k-NN respectively.

Therefore, experiment results show that thanks to the integration of HMM, single discriminative learning models, ranging models and particle filter methods, PF-ELM outperforms

KF, NLST, and k-NN for accuracy and stability. Unlike KF and NLST, PF-ELM is able to reduce the negative influence of multi-path effects in NLOS conditions. Moreover, PF-ELM outperforms traditional fingerprinting localization methods (e.g., k-NN-based) by combining fingerprinting models and range-based localization methods.

VI. CONCLUSIONS

This work proposed an ensemble learning model to achieve high zone prediction performance. Our zone detection model integrates HMM with discriminative learning techniques. LOS and NLOS Wi-Fi propagation conditions are identified based on the zone detection method. Further, we fuse zone detection information with an enhanced radio-based ranging model, IMU, and floor plan information to achieve high indoor localization performance. Real-world indoor environment evaluation results indicate that our approach is more accurate and robust than traditional indoor localization methods.

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