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Improved particle filter based on WLAN RSSI fingerprinting and smart sensors for indoor localization

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ABSTRACT

Received Signal Strength Indicator (RSSI) is affected significantly by multi-path fading, building structure and obstacles in indoor environments, which lead to similar fingerprints problem and noise. To improve the performance of traditional fingerprinting method, the measurements provided by inertial sensors can be leveraged. Particle filter (PF) method is a widely chosen algorithm for sensor fusion. However, the initialization and weighting process are problematic in indoor positioning systems. This paper proposes a new PF scheme which yield a smooth and stable localization experience. To differentiate similar fingerprints, a single-hidden layer feed-forward networks (SLFNs) is used to model the multiple probabilistic estimations and improve the performance of the PF. Meanwhile, a new initialization algorithm using Random Sample Consensus (RANSAC) is presented to reduce the convergence time. Experimental measurements were carried out to determine the performance of the proposed algorithm. The results indicate that the positioning error of proposed scheme falls to less than 1.2 m which is better than the error reported in comparable approaches.

1. Introduction

The demand for accurate positioning for indoor location based services (LBS) is growing rapidly. The GPS technology cannot be easily used for indoor positioning as the direct line of sight obstructed which reduces the positioning accuracy [1,2]. To overcome the challenges of indoor positioning, many techniques have been developed in the past few years. The reported indoor positioning methods fall into two main approaches. In the first approach, wireless signals such as Bluetooth, Zigbee, RFID, Ultra-Wide Band (UWB), Wireless Local Area Network (WLAN) [3] are leveraged for indoor positioning in the second approach inertial sensors are utilized [4].

Two methods are developed for positioning algorithms utilizing wireless signal techniques. In the first method, the distance is estimated from Time of Flight (ToF), Time of Arrival (ToA)/Time Difference of Arrival (TDoA), Angle of Arrival (AoA) or Received signal Strength Indicator (RSSI) [3]. RSSI for ranging is highly dependent on the environment structure and has limited accuracy [5]. Time measurement based method supports high positioning accuracy but it commonly requires extra infrastructure to accurately measure the time difference. This requirement increases the cost of implementation. An infra-structure free solution which utilizes available wireless local area network (WLAN) have also been reported [6]. In this method, it is assumed that each reference point has a unique RF signal strength vector, which is also called fingerprint. The fingerprints of reference points in a building are collected ahead of time and stored in a database. Then, pattern recognition algorithms are used to match the on-line vector with pre-collected fingerprints. This approach is infrastructure-free but labor-intensive [7]. Moreover, this system normally cannot provide a smooth location estimation because it suffers from problems such as similar fingerprints [8], missing value and noisy RSSI value.

In the sensor based indoor positioning method, the key task is to estimate the travel distance and angle of humans or objects [4]. As the inertial measurement unit (IMU) which comprises accelerometer, gyroscope, compass and barometer is widely integrated in portable devices, many researchers have dedicated their work to develop new IMU based solutions for indoor positioning. The common algorithm of IMU assisted positioning is Pedestrian Dead Reckoning (PDR). In this method, a step sensor which is implemented by accelerometer, is used to detect the displacement of a user. Meanwhile, the gyroscope and/or compass are used to detect the orientation [9]. The cost of this method is very low and a smooth location estimation is achieved. However, as the classic PDR algorithm cannot calibrate itself, it suffers from cumulative error problem.

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To tackle this problem, algorithms that combine Wi-Fi fingerprinting and IMU assisted positioning have been explored by researchers. Inherited from robotics community, standard Kalman Filter (KF), Particle Filter (PF) and their variants are introduced to fuse the sensor information [10]. In general, KF is applicable to linear and Gaussian models. For complex noisy environments, PF is widely chosen for its superiority in handling nonlinear system and non-Gaussian noise [11]. The idea behind KF and PF is that these filters take use of a series of noisy and inaccurate measurements to produce the estimations of uncertain positions of a moving object. The result is proved to be better than using a single inaccurate measurement.

Although, the results after combining fingerprinting and IMU are smooth and self-calibrated, the accuracy is still restricted since fingerprinting algorithm requires the assumption of unique fingerprints [8]. In practice, due to the multi-path effect and the arrangement of the location of access points (APs), two distant reference points may share very similar fingerprints. As a result, the pattern recognition algorithms cannot guarantee the correct estimation. An inaccurate position estimation can deteriorate the overall performance. Meanwhile, the time required to initialize PF is also an important factor. Global initialization has a slow convergence speed. Deploying extra hardware at entrances increases the total cost.

There are two major contributions on improving particle filter in this paper. First, RANSAC-based approach [12] is performed to get rid of the inaccurate estimations from Wi-Fi fingerprinting during initialization phase. It requires much less iterations to converge compared to global initialization. The algorithm selects the inliers from fingerprinting estimations by a Gaussian model established by PDR data. Then take use of the inliers to estimate the initial location. Experimental results show the proposed method reduces required initialization iterations by 8.1 and reduces 1.5 (m) error distance. Second, to overcome the problem of wrong estimations after initialization, the weighting portion of the conventional PF is improved in the proposed method to model multiple fingerprinting probabilities by SLFNs interpolation [13]. The probabilities of different reference points from Wi-Fi fingerprinting algorithm are considered to minimize the error introduced by similar fingerprints problem. SLFNs interpolation is performed to interpolate the probability of multiple results and then the PF weighting based on the interpolated model is started. Proposed method show 1 (m) error distance reduction compared to convention method in the experiments.

The rest of the paper is organized as follows. A description of the related works and motivations is provided in the next section. Section 3 introduces the preliminaries of this paper. Section 4 presents the RANSAC-based initialization approach and a novel particle filter weighting scheme by SLFNs interpolation. Simulation and experimental results are demonstrated in Section 5. Section 6 concludes the paper.

2. Background

2.1. Related work

For infrastructure-free indoor localization, fingerprinting based method is very popular and well-studied. In fingerprinting based methods, deterministic approaches and probabilistic approaches are two major approaches that utilize the pre-collected RSSI fingerprints for location estimation. Deterministic approaches mainly apply the concept of classification or regression from pattern recognition. Bahl and Padmanabhan proposed RADAR system [6] which was based on the K-Nearest-Neighbor (KNN) and reported acceptable accuracy. Support Vector Machines [14] were also implemented due to its superb classification and regression ability for non-linear problems. Probabilistic approaches improve the stability against RSSI variation by modeling the RSSI distribution of certain APs. Youssef et al. proposed Horus system that implemented such approach that reported a higher accuracy and stability. However, very accurate RSSI distribution for each AP is not practical to achieve and a biased distribution can degrade the accuracy. The main limitation of fingerprinting methods is the sensitivity to the RSSI variation caused by multi-path effect and large-scale fading effect [15].

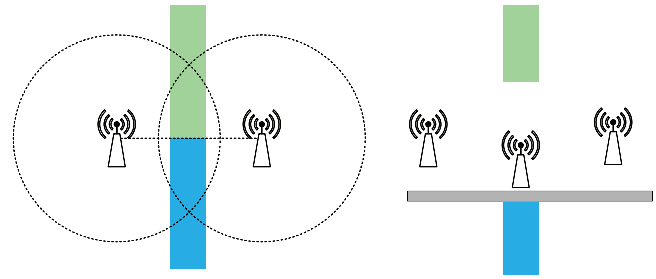

Fig. 1. Scenario of similar fingerprints. Blue region and green region in each graph show similar fingerprints due to the deployment of APs and the building structure. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

PF has been implemented by many indoor positioning systems to deal with the noise introduced by PDR algorithm. These systems mainly differ in the initialization phase of PF and the chosen of landmarks. Travi-Navi [16] utilized PF to fuse the data from different sensors and camera and received a good performance. However, for initialization phase, it only generates particles around the entrance of the indoor space. If a client starts from inside of the building, it is unlikely for the system to get proper initialization. It also took use of vision as a kind of landmark, which is heavy power consuming. System Zee [17] leveraged augmented particle filter, which employ global initialization and map matching techniques (turning around the corners and hallways). Global initialization usually requires a large amount of particles which spread around the whole indoor space. This method has a slow convergence rate since it requires corner match on the map. It is also computational heavy when the map is large.

Some calibration-free systems such as Travi-Navi, Zee [16–18] have also been developed. These systems take use of PDR algorithms and other real-time sensor data to achieve calibration-free purpose. These work has certain limitations as well. They rely on the map information heavily. The system hinges on the Indoor environments that indeed offer the requisite number of landmarks. This criterion is highly dependent on the specific environment.

There are a few works dedicated to the fusion of fingerprinting methods and PDR algorithm. Leppäkoski et al. suggested Extended Kalman Filter and PF for the fusion and got improved performance, yet the system requires a known initial point [10]. An upgraded PF with a fallback filter for particles initialization in which the filter requires a heavy global state space search is proposed in [19]. The method developed in [20] takes processed Wi-Fi RSSI for azimuth estimation and PF initializes uniformly in particle space. None of these works specifies particular mechanism to handle the occasional poor observation from fingerprinting.

2.2. Motivation

The motivation of this paper is three-fold. Firstly, preferred method should make sure that the PF does not miss the optimal result. Traditional fingerprinting methods only deliver one estimation in terms of RSSI fingerprints. Because of the noisy indoor environment, missing value and the similarity among the fingerprints, it might be distant from the correct estimation so that particles follow the wrong estimation. As shown in Fig. 1, there is no means that fingerprinting methods can differentiate the blue region and green region. When the system produces the wrong estimation, the accuracy of predicted trajectory from PF degrades. Second motivation is how to weight the particles based on the solution from fingerprinting methods. The weights for particles shall be smooth and continuous so that the movement of particles can be smooth in accordance with human activity. Thirdly, the method shall offer accurate initial guess for PF without any aid from extra-hardware. The accurate initial guess enables the system to acquire a faster convergence rate and a more accurate location estimation.

3. Preliminaries

3.1. Indoor localization problem setting

Particle filter based indoor localization problem is to find the joint posterior $p(v_{1:t}|z_{1:t}, u_{1:t}; m)$ about the trajectory $v_{1:t}$ of user in the indoor environment at time t. In this problem, the $z_{1:t} = z_1, \ldots, z_t$ are the observations and $u_{1:t} = u_1, \ldots, u_t$ are the motion odometry measurements. Map m is usually known in the system. The motion odometry measurements are usually obtained by the IMU module. PDR is a common methodology implemented for human navigation. There are multiple methods to get the observations including laser range finder, infrared, Wi-Fi fingerprinting etc. In this paper, we mainly focus on the solution by Wi-Fi fingerprinting.

3.2. Particle filter with fingerprinting algorithm

3.2.1. Sampling importance resampling particle filter

Particle filter is a popular technique to localize robots with unknown position. In particle filter, each particle is a pose hypothesis of the current state. These states are randomly generated in the estimated area. Based on the RSSI measurements, the particles are first given different weights. Then these particles are selected according to the corresponding weight. This process filters out those states with low probabilities. The remaining particles are more likely to present the distribution of the actual position. Proposed by Gordon et al. [21], Sampling Importance Resampling (SIR) particle filter is widely used because it keeps the diversity of particles. A SIR filter processes the sensor observation and motion odometry readings iteratively when the data is available. In every iteration, it updates and resamples all the particles which represents the posterior of the trajectory. Each iteration can be demonstrated by the following steps.

- Sampling: Given the previous trajectory v_{t-1}, odometry measurements u_t, the observations z_t, the map m and the number of samples Q, for $q = 1, \ldots, Q$, the particles of next time slot are obtained by drawing samples from the proposal distribution $\pi(v_t^{(q)}|v_{t-1}^{(q)}, z_t, u_t; m)$.
- Importance weighting: All the particles are weighted by the importance weights $w_t^{(q)}$, calculated from

$$w_t^{(q)} = w_{t-1}^{(q)} \frac{p\left(z_t|v_t^{(q)}\right) p\left(v_t^{(q)}|v_{t-1}^{(q)}, u_t\right)}{\pi\left(v_t^{(q)}|v_{t-1}^{(q)}, z_t, u_t; m\right)}. \quad (1)$$

  Then the weights are normalized. Weighting has a major effect on the final performance. Incorporated with Wi-Fi fingerprinting methods, traditionally the likelihood of observation $p(z_t|v_t^{(q)})$ is a Gaussian distribution on the observed location. Unlike the observation made by sensors from robotics, this observation is not so accurate and stable. Special steps shall be done to handle the unreliable observations.
- Resampling: Resample q particles from existing particle set with proportional to their weights. It is used to avoid the particle degeneracy. It is necessary to keep an adequate number of particles to approximate the actual prior distribution.

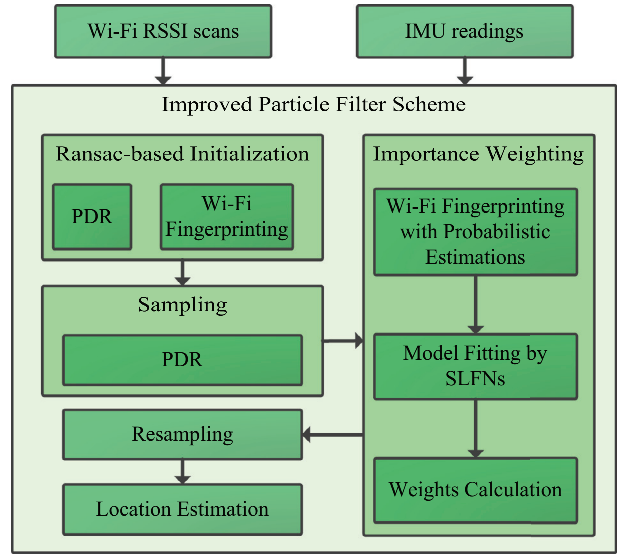

Fig. 2. A new particle filter scheme by improved initialization phase and improved weighting process.

The role of PF in this system is to combine the PDR estimation with fingerprinting estimation. Whereas it remains open about how to decide the likelihood of observation from fingerprinting estimation.

3.2.2. Wi-Fi RSSI fingerprinting methods

Wi-Fi RSSI fingerprinting methods are mainly used to deliver the observation $z_{1:t} = z_1, \ldots, z_t$ to the system. The output can be a grid or a set of coordinates, which corresponds to classification or regression. As for classification, collect k samples with labels from N reference points (RP) as the training data. For $n \in [1, 2, \ldots, N]$, the label is denoted as $\mathbf{l}_n = (\hat{x}_n, \hat{y}_n)$. The parameters $\hat{x}_n$, $\hat{y}_n$ are the geographical coordinates of the corresponding RF. Suppose there are $\bar{m}$ Wi-Fi APs around the environment. In RSSI fingerprinting problem, z_t is defined as a vector: $\mathbf{z}_t = \{SSI_1, SSI_2, \ldots, SSI_{\bar{m}}\} \in \mathbb{R}^{\bar{m}}$. All the samples are used as RSSI fingerprints to construct the fingerprints database. The positioning problem is to find the label $l_t(\hat{x}_t, \hat{y}_t)$ at time t, given the RSSI fingerprint $\mathbf{z}_t$. The interpretation of regression is similar to the classification except that the regression requires the numeric solution, which are the user's coordinates on the map.

4. Particle filter with RANSAC-based initialization and improved weighting scheme

As depicted in Fig. 2, the inputs of the system include Wi-Fi RSSI scans and IMU readings. Two major improvements are applied to traditional particle filter. Firstly, a RANSAC-based initialization phase is introduced to the system. This method requires several scans from Wi-Fi module and a trajectory model made by PDR algorithm. It filters out all the outliers by the trajectory and keeps the inliers for initialization, which increase the convergence rate of the PF as well as the accuracy. After a normal sampling phase, an improved importance weighting method is introduced. This phase initially collects multiple fingerprinting estimations with their probability. Then perform model fitting algorithm to construct a Gaussian mixture model. Each particle obtains a weight from the constructed model. Finally, resample the particles based on the weights and calculate the average location from the new particles.

4.1. RANSAC-based Initialization

Using RSSI fingerprinting to initialize the particle filter, there is no requirement for extra hardware. A faster convergence speed is available compared to global initialization. Normally, multiple scans are required for obtaining stable estimations. Whereas because of the noisy indoor environment and the similarity among fingerprints, outliers are always observed during the initialization phase. There is even a small chance that the PF initializes in a completely wrong area and therefore produces all wrong results.

To tackle this issue, we introduced Random Sample Consensus (RANSAC) with PDR trajectory. As an iterative algorithm, RANSAC is widely used in computer vision and regression problems [22]. It harnesses regression techniques to generate models. It retains the inliers that can be fit into the model while filter out the outliers. Unlike pure regression techniques, it has the ability to deal with contaminated dataset. It comprises two phases: model generation and model evaluation. In the model generation phase, it randomly picks up a subset of data for multiple times then model each of them. The models are generated based on the prior of the application. Then the model is evaluated and finally keeps the one with the most inliers during the evaluation phase.

The implementation of RANSAC is based on two assumptions: outliers from the samples are minority and a model is available to fit the inliers. Both of these assumptions are satisfied in indoor positioning scenario. Firstly, for fingerprinting algorithms, the reported average error distance is in meter range, generally about 1–5 m [23]. According to the error cumulative distribution function (CDF) of classic fingerprinting algorithms [6,24], it is observed that the error distance of over 90% of the estimations are less than 4–5 m, which means that majority of the estimations are inliers. These reported results meet the experimental results of this paper. Secondly, a natural model is given by the trajectory from PDR algorithm. The variables are $(\hat{x}, \hat{y})$ that determines the initial point of the trajectory.

Pseudo-code for RANSAC-based initialization is detailed in Algorithm 1. The input of this algorithm is a set of fingerprinting estimations Ψ. The model is constructed by PDR trajectory M_{PDR} and a few experienced parameters. Steps 2 and 3 are the model generation phase. The algorithm randomly selects *min* data points to the set of inliers $S^{(\bar{u})}$ from dataset Ψ. With the given model, it runs model fitting algorithm for data points $S^{(\bar{u})}$. Note that PDR trajectory is a perfect model to be used since the error of IMU is quite small in a short time interval. The parameter of the model is $\hat{x}, \hat{y}$ which denotes the initial point of user. Then the model evaluation phase starts. The error distance of all the data points from set $\Psi - S^{(\bar{u})}$ are calculated and compared with model tolerance factor ϵ. Those with error distance smaller than ϵ are added to *S*. Finally, if $\bar{u}$ is greater than *k*, algorithm returns. Otherwise repeat all the steps until reach the maximum iterations *N*.

Algorithm 1 RANSAC-based initialization algorithm.

INPUT: Data of fingerprinting estimations: Ψ
INPUT: Model from PDR: M_{PDR}
INPUT: Maximum iterations: N
INPUT: Minimum data points to fit the model: *min*
INPUT: Model tolerance factor: E
INPUT: Inlier threshold number: I_{th}
OUTPUT: Inlier dataset $S^{(\bar{u})}$ and fitted model $M_{PDR}(\hat{x}, \hat{y})$

```
1:  while iterations < N do
2:      Randomly select S^(ū) from Ψ, ū = min
3:      Fit d_i to model M_PDR(x̂, ŷ)
4:      for d ∈ Ψ − S^(ū) do
5:          Calculate Error(d; M_PDR(x̂, ŷ))
6:          if Error(d; M_PDR(x̂, ŷ)) < E then
7:              ū + +
8:          end if
9:      end for
10:     if u > Ith then
11:         return M_PDR(x̂, ŷ), S^(ū)
12:     end if
13: end while
```

4.1.1. Model generation

To construct the PDR model, we first perform PDR for *c* iterations. For each iteration, the relative position of user can be computed by

$$(x_{i+1}, y_{i+1}) = (x_i + L_i * sin(\phi_i), y_i + L_i * cos(\phi_i)) \tag{2}$$

where x_i and y_i are the coordinates, L_i and ϕ_i are the stride length and heading at the *i*th step. Gaussian least squares fitting are leveraged to fit the trajectory to a Gaussian model $G(x)$. Note that $G(x)$ has certain domain $x \in [x_{min}, x_{max}]$. $G(x)$ is described by

$$G(x) = \sum_{i=1}^{\hat{n}} a_i e^{[-(\frac{x-b_i}{c_i})]^2}, x \in [x_{min}, x_{max}] \tag{3}$$

where $\hat{n}$ is the number of terms, a_i, b_i, c_i are the coefficients of Gaussian model and x_{min}, x_{max} are the minimum and maximum values of the PDR trajectory. To shift the function to arbitrary position on the map, two coefficients of (x', y') are introduced to estimate the initial point. As a result, (3) is transformed to

$$M_{PDR}(x', y'; x, y) = \sum_{i=1}^{\hat{n}} a_i e^{[-(\frac{x-x'-b_i}{c_i})]^2} + y', \tag{4}$$

where $x \in [x_{min}, x_{max}]$. In order to find $(\hat{x}, \hat{y})$, the algorithm requires to estimate the initial point by Wi-Fi fingerprinting during initialization period which minimize the estimation errors. Applying the selected *min* number of fingerprinting estimation *S* from Ψ, $(\hat{x}, \hat{y})$ becomes

$$\arg\min_{(x,y)} \sum_{d \in S^{(\bar{u})}} Distance(d; M_{PDR}(x, y))^2, \tag{5}$$

where $Distance(d; M_aPDR(x, y))$ is the distance between the instance and the model. As $M_{PDR}(x, y)$ is a curved line segment, the distance from point $A(x_A, y_A)$ to a curve is calculated by

$$D(x_A, y_A) = \sqrt{(x - x_A)^2 + (y - y_A)^2}, \tag{6}$$

Let deviation of (6) equals to 0, then get the closest point *o* on the curve (x_o, y_o). Finally calculate $Distance(d; M_aPDR(x, y))$ by

$$Distance(d; M_{PDR}(x, y)) = \begin{cases} \sqrt{(x_o - x_d)^2 + (y_o - y_d)^2} & x_o \in [x_{min}, x_{max}] \\ C & \text{otherwise} \end{cases}, \tag{7}$$

where *C* is the minimum value of the distances from *d* to the two endpoints.

4.1.2. Model evaluation

RANSAC considers the evaluation problem as an optimization problem formulated as

$$\hat{M}_{PDR}(\hat{x}, \hat{y}) = \arg\min_{M_{PDR}(\hat{x}, \hat{y})} \sum_{d \in \Psi} Loss(Error(d; M_{PDR}(\hat{x}, \hat{y}))), \tag{8}$$

where Ψ is the data of fingerprinting estimations, $M_{PDR}(\hat{x}, \hat{y})$ is the generated model with parameter $(\hat{x}, \hat{y})$, *Loss* and *Error* are the loss function and error function respectively. In RANSAC, the loss function is defined as:

$$Loss(Error(d; M_{PDR}(\hat{x}, \hat{y}))) = \begin{cases} 0 & |Error(d; M_{PDR}(\hat{x}, \hat{y}))| < \epsilon \\ 1 & \text{otherwise} \end{cases}. \tag{9}$$

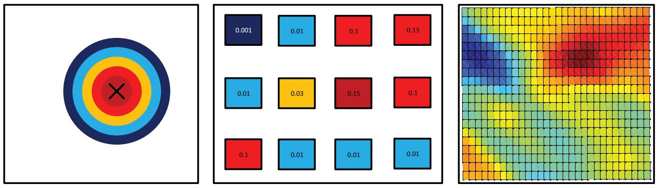

Fig. 3. (a) Traditional Gaussian distribution weighting. (b) Discrete probabilities on different reference points. (c) SLFNs interpolation weighting.

4.2. Modeling fingerprinting probabilities by SLFNs interpolation

In Eq. (1), it is mentioned that the likelihood $p(\mathbf{z}_t|v_t^{(q)})$ normally is approximated as Gaussian distribution around the reference point that has the highest probability. The probabilities of other reference points are abandoned. In order to keep all the useful information, the proposed method takes use of the probabilities on all the reference points.

Fingerprinting method is used to get the probability $P(\mathbf{z}_t|\hat{x}_n, \hat{y}_n)$. Different pattern recognition algorithms are able to achieve this purpose by different methodologies. The most straightforward methodology is the Bayesian scheme. Normally, this methodology is to search the RF that gives the highest probability:

$$\arg\max_{i \in [1:n]} P(\mathbf{z}_t|\hat{x}_i, \hat{y}_i). \tag{10}$$

In proposed PF, the whole set of $P(\mathbf{z}_t|\hat{x}_n, \hat{y}_n)$ is leveraged to keep the entire information of fingerprinting method such that the particles are able to track the real location. In order to calculate the probabilities, one can use probabilistic methods [24] or deterministic methods such as Support Vector Machines (SVMs) [25].

For probabilistic methods, the Gaussian distribution can be used to approximate the distribution of RSSI of one AP at a certain location. $P(\mathbf{z}_t|\hat{x}_n, \hat{y}_n)$ is calculated by $\prod_{m=1}^{l} f_m(SSI_m; \mu_m, \sigma_m)$, where f_m is Gaussian distribution of AP m with mean μ_m and variance σ_m^2. Mean and variance values are determined by training data. Finally, probability $P(\mathbf{z}_t|\hat{x}_n, \hat{y}_n)$ is normalized.

For SVMs, a pairwise coupling method [26] from LIBSVM [27] is widely used for probability estimation. As a two-class classifier, SVMs requires pairwise coupling to extend the two-class probability scheme $a_{ab} = P(\mathbf{z}_t|i = a \text{ or } b)$ to multi-class probability $P(\mathbf{z}_t|\hat{x}_n, \hat{y}_n)$. Essentially, it is achieved by solving the optimization problem given by

$$\min_P \sum_{i=1}^{N} \sum_{j:j\neq i} \left(a_{ji}P(\mathbf{z}_t|\hat{x}_i, \hat{y}_i) - a_{ij}P(\mathbf{z}_t|\hat{x}_j, \hat{y}_j)\right)^2$$
$$\text{subject to} \sum_{i=1}^{n} P(\mathbf{z}_t|\hat{x}_i, \hat{y}_i) = 1, P_i \geq 0, \forall i, \tag{11}$$

where $a_{ij} + a_{ji} = 1, \forall i \neq j$. $P(\mathbf{z}_t|\hat{x}_n, \hat{y}_n)$ is obtained by solving (11).

As given in Fig. 3(a), the traditional weighting scheme is based on Gaussian distribution on the RP with highest possibility. The particles are weighted based on the distance to that RP. However, when this estimation is with large error due to noise or similar fingerprints issue, the results of particle weighting process are biased. It is preferred to keep the probabilities on all the RF, $P(\mathbf{z}_t|\mathbf{l}_n)$. The probabilities of different RFs are illustrated in Fig. 3(b). It can be seen that other RPs that also have high probabilities are kept so that the particles are not biased to one single RP. As the fingerprints are collected discretely, only those particles on the RPs have probabilities values. A continuous weighting model is required. SLFNs interpolation is introduced to interpolate the possibility model. The output is given in Fig. 3(c). A continuous model is produced by the interpolation technique.

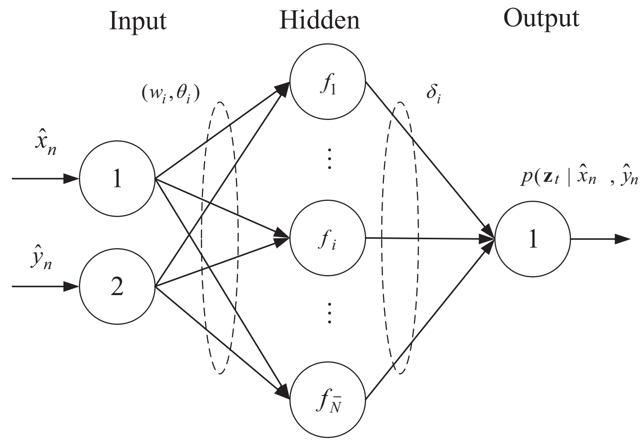

Fig. 4. Architecture of the SLFNs interpolation.

The reason why this process can deal with similar fingerprints problem is that it evaluates all the RFs and delivers all the corresponding probabilities to the weighting process of PF. When there are similar fingerprints that are distant from each other, particles are able to differentiate them after the weighting and resampling process. SLFNs based interpolation is selected for two reasons. The first reason is that arbitrary target function is required since $P(\mathbf{z}_t|\mathbf{l}_n)$ does not follow any certain distribution. Second, the error should be extremely small. Based on the literature [28], the SLFNs are able to approximate any target distribution with arbitrary small error. It has been proved in [29] that SLFNs can interpolate samples with negligible error.

The mathematical expression of SLFNs with $\bar{N}$ hidden nodes and activation function $f(x)$ on this interpolation problem is given as

$$P(\mathbf{z}_t|\mathbf{l}_n) = P(\mathbf{z}_t|\hat{x}_n, \hat{y}_n) = \sum_{i=1}^{\bar{N}} \delta_i f(\mathbf{w}_i \cdot (\hat{x}_n, \hat{y}_n) + \theta_i), \tag{12}$$

where $\mathbf{w}_i \in \mathbb{R}^2$ and $\delta_i \in \mathbb{R}$ are the input weight vector and output weight vector that connect the ith hidden node with the input and output. $\theta_i \in \mathbb{R}$ is the threshold of the ith hidden node. Note that $(\hat{x}_n, \hat{y}_n)$ are two input nodes, and the interpolated probability $P(\mathbf{z}_t|\hat{x}_n, \hat{y}_n)$ is the output node. The architecture of such SFLNs is shown in Fig. 4.

To use SLFNs interpolation in real time applications, Extreme Learning Machine (ELM) is recommended. There are two major advantages of ELM. (1) It has an extremely fast learning speed. The training time is in the range of miliseconds. (2) ELM network supports small training error for any given training set, while the hidden neurons is no larger than the number of training samples [30]. The speed of ELM is fast mainly because it randomly generates the hidden neurons including the number and the weights. The details of ELM is given in [31] and source code is also available.

5. Experimental results

Simulations and experiments were conducted to verify the efficiency of the PF scheme at the second floor of Centre for Engineering Innovation of University of Windsor. PDR data and fingerprinting data were collected. The experiment was conducted at a time where people were inside the building and the RSSI samples were affected by environmental factors such as moving objects and people. Therefore, the RSSI fingerprinting based approach suffers from multi-path effect and moving objects significantly. This is similar to a practical scenario case. The PDR algorithm is implemented on cell phone using the data collected by IMU. We applied these data

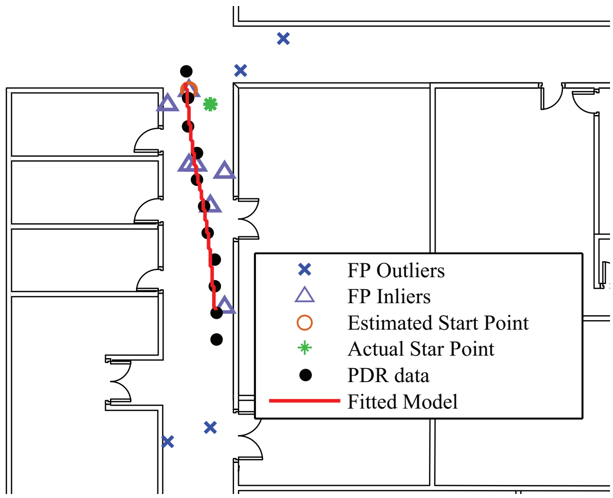

Fig. 5. Fitted model of RANSAC initialization.

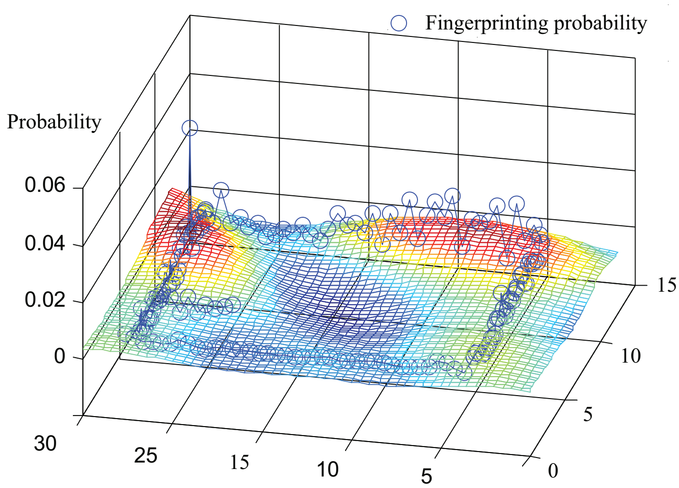

Fig. 6. SFLNs interpolation on fingerprinting probabilities.

to test the initialization phase and the estimation accuracy of the proposed PF scheme. For fingerprinting algorithm, a total of 84 reference points were selected with one meter interval in a 30 (m) by 35 (m) area. 30 fingerprints were collected at each reference point. As comparison, SVM and probabilistic algorithm are selected.

5.1. Experiment on initialization phase

To test the proposed initialization approach, we collected 10 datasets under initial condition at 10 different places with different tracks. Each initial dataset includes 11 steps as well as 11 Wi-Fi scans. We first examine the Gaussian model fitting on each dataset. Fig. 5 shows examples of the fitted model from PDR data. Number of terms is determined by RMSE. We set the threshold of RMSE to be 0.1 and select the lowest number of terms when satisfy the threshold. Then we apply the model to filter out the outliers of Wi-Fi fingerprinting estimations. As denoted in Fig. 5, inliers are distinguished by the proposed RANSAC approach. Finally, the estimated start point is marked on the graph. PF is initialized on the current location of the acquired model. The simulation results of this experiment are listed in Table 1. RMSE of PDR model fitting is used to test the precision of the model compared to PDR trajectory. It is shown that the average RMSE is 0.21 (m). Number of outliers demonstrates the effectiveness of the RANSAC approach. In this experiment, proposed method filtered out 4.2 outliers in average. Initialization error distance and maximum error distance illustrate the initialization accuracy. As a comparative algorithm, KNN based fingerprinting initialization is selected. Proposed method reduced the average error distance by 1.6 (m) and reduced maximum error distance by 2.6 (m).

For convergence speed, proposed method only requires these 11 iterations to perform model fitting and RANSAC algorithm. As a comparison, the global initialization requires 19.1 iterations in average to converge.

Table 1
Initialization experiment results.

	Proposed method	Fingerprinting initialization
Average RMSE of PDR model fitting	0.21 (m)	–
Average number of outliers	4.2	–
Average initialization error distance	1.1 (m)	2.7 (m)
Maximum initialization error distance	2.6 (m)	5.1 (m)

Table 2
Error distance of different methods.

Methods	Average error distance (m)	Maximum error distance (m)
SVM [14]	3.2	9.3
Probabilistic algorithm [24]	3.4	11.2
PDR and probabilistic algorithm fused by PF	2.2	4.1
Proposed method using SVM	1.2	2.9
Proposed method using probabilistic algorithm	1.3	3

5.2. Experiments for testing proposed PF scheme

In this experiment, all the algorithms use the same fingerprints database and the same PDR data. Fig. 7(a) shows the pedestrian trajectory estimated by original fingerprinting method. Consecutive estimations are connected by red lines. It can be seen that the results suffer from inconsistent observations and estimations. In some cases, the continuous estimations are distant from each other due to the missing value, noisy data or the similarity of the fingerprints. Fig. 7(b) demonstrates the trajectory from original PDR. In this figure, each red dot represents one step. This approach performs well during first three hallways and then accumulates large errors. Fig. 7(c) shows the trajectory of proposed method, which combines the information from fingerprinting and PDR. It is shown that the algorithm fixes the noisy fingerprinting data and PDR data and improves the final performance. Proposed PF scheme leverages SLFNs for probability distribution model construction shown in Fig. 6. This surface is employed to perform particles weighting phase. Each particle is able to acquire a probability based on its location. Those particles with higher probability are more likely to be saved after resampling phase.

As Table 2 shows, the average error distances of proposed method with SVM and probabilistic algorithm are 1.2 (m) and 1.3 (m) respectively. This value is about 1 (m) lower than the value of PDR and probabilistic method fused by PF using classic Gaussian weighting. It also shows great improvements on the maximum error distance. As given in Fig. 7(a), at some points the fingerprinting algorithm provides distant estimations, which results in a high maximum error distance. This phenomenon cannot be seen from the trajectory of proposed method.

Table 3 shows the comparison among proposed method and other localization systems. Proposed method has advantages on

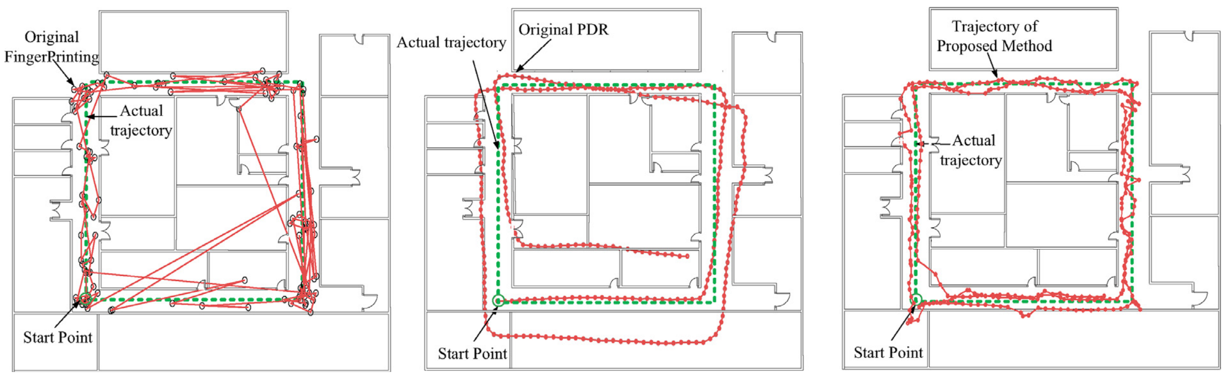

Fig. 7. Trajectories of (a) fingerprinting method (SVM), (b) PDR, (c) proposed method.

Table 3
Comparison with other localization methods.

	PF initialization	Convergence time	Method	Accuracy	Drawbacks
Zee [17]	Global initialization	Require a few corners, up to a few minutes	Magnetic field sensor, map info, Wi-Fi, PDR, PF	Meters	Slow convergence time, require map info, high complexity in big map
Travi-Navi [16]	Entrance initialization	Require a few corners, up to a few minutes	Magnetic field sensor, map info, Wi-Fi, PDR, PF, vision	Meters	Start point is limited, high power consumption, high complexity
Unlock [18]	N/A	N/A	Magnetic field sensor, map info, Wi-Fi, PDR	1–2 (m)	Require requisite landmark density, require map info
Li et al. [32]	Manual initialization	N/A	Map info, PF, PDR	1.5–2 (m)	Manual initialization, require map info
Proposed method	RSS based initialization	A few seconds	Wi-Fi site survey, PF, PDR	1.2 (m)	Require site survey

initialization, convergence time and accuracy (All the accuracy values are taken from reference papers). Other systems suffer from initialization method, complexity, require number of particles and environment dependency. Even though the proposed method requires Wi-Fi RSSI site survey, it still can be chosen for many scenario. For some indoor scenario, the site survey is already available since fingerprinting has been a popular method in recent years. Proposed particle filter can be an effective algorithm to improve the performance of fingerprinting method. A rapid auto-initialization phase is crucial since the users only require a few minutes to arrive the destination in many scenario. Minutes of initialization time is not acceptable.

6. Conclusion

In this paper, a new particle filter with a hardware-free initialization phase is presented to improve the accuracy of indoor location positioning using received signal strength. The hardware-free initialization is implemented by RANSAC algorithm. This algorithm filters out outliers from the fingerprinting estimations by a constructed PDR model. Inliers are remained to acquire the initial point and the current location. The PF is initializing based on the current location. This initialization phase achieves 1.1 (m) average error distance in the experimental demonstration. For enhancing the fusion of fingerprinting and PDR, we proposed a SFLNs based model fitting algorithm. The algorithm takes advantage of the probabilities of all the reference points from fingerprinting method. The algorithm fits a SFLNs model to the probabilities and constructs a probability surface over the interested area. The particles are weighted by this continuous surface to reduce the error. This approach makes sure that the particles would not suffer from the similar fingerprints issue. The experimental results show about 1.2 (m) average error distance in compare to 2.2 (m) in comparative methods.

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