A Novel Indoor Tracking Algorithm Based on Particle Filter

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Abstract. Nowadays target tracking has become a hot issue of indoor positioning in the military or civilian areas. Due to the nonlinear characteristics of the indoor environment, there exist some difficulties in indoor tracking scheme. In this paper, we proposed an indoor tracking algorithm based on particle filter. RSS values were severed as the observed values and the naive Bayesian algorithm was used to collect RSS samples for estimating the probability density distribution as a location fingerprinting in our proposed algorithm. Then a system of track model was created. Moreover, particle filter was introduced in order to process positioning error which was brought by system noise and observation noise and solve tracking problems of mobile terminal. Experimental results show our algorithm achieves great accuracy and robustness in tracking trajectory aspect and performs better than the tracking algorithm using Kalman filter.

Introduction

With the development, maturity and popularity of IEEE802.11 and wireless communication technology, the location-based services (LBS)[1] presents a significant growth trend. In the outdoor environment, Global Positioning System (GPS) can the service of global, all-weather, high precision, high efficiency and multi-function, including the accurate positioning. But in the complex indoor environment, GPS signal can not apply to effective location targeting, because they are too weak to penetrate the walls and are reflected and scattered by the various items so that inevitable decay will be generated. So it is practical to develop a positioning system, which can maintain real-time and high-accurate estimation of location.

As far as we all know, WLAN has been widely deployed and had low system costs. Even if there are a huge number of terminals (such as mobile phones, laptops, etc.), it also has good communication capabilities. So WLAN-based indoor positioning is a technique that can reuse current available WLAN infrastructure without additional installation and hardware costs to solve the problem of positioning issues in the indoor environment.

In the former researches, most of them concentrate on the WLAN-based positioning technology. It makes use of the received signal strength (RSS) from the access points (APs) to create a location fingerprint database, where a mapping between a location fingerprint and a location is established. Then it adopts the fingerprinting matching algorithms to estimate the position, such as K nearest neighbors algorithm (KNN)[2] and Naive Bayesian algorithm[3~7] . However, because of the noise and serious multipath caused by the complex indoor environment, those algorithms mainly focus on the static positioning and can't provide high-accurate positioning.

Actually, it is very vital for us to tracking mobile terminals in many situations. If the algorithms referred before are used, it is hard to achieve the accurate location. Some researches [8][9] adopt Kalman filter to improve the tracking performance, where it is assumed that the location estimation error follows the Gaussian distribution. However, in fact, the location estimation error distribution is difficult to be determined so that the tracking performs worse. So we propose a novel particle filter tracking algorithm in WLAN indoor environment.

Particle filter [10][11] is an approximate method based on sequential Monte Carlo (MC) method.

The key idea is that the required posterior probability distribution can be represented by a set of random particles associated with their weights. Moreover, the larger the number is, the closer the particle filter approaches the optimal Bayesian estimation. Due to the non-parametric characteristics, it breaks the constraint of Gaussian distribution which random variables must follow to solve the problem of nonlinear filtering. So it also works well in non-linear and non-Gaussian systems.

The paper is organized as follows. Section II describes the state-space model including the movement model and the observation model. In section III, the tracking algorithm based on particle filter is introduced. Section IV gives the results and analysis of the simulation. Finally, conclusions of this paper are presented in section V.

State-space Model

Movement Model.

On the premise of tracking the mobile terminal, firstly the movement of the mobile terminal should be described with the motion model. It is assumed that the mobile terminal moves in the two-dimensional plane and the samples are taken each T seconds. Then the state equation can be written as

$$X_k = GX_{k-1} + \varepsilon_k, \varepsilon_k \sim N(0, \sigma_a^2 A) \tag{1}$$

Where $X_k = (x_k, y_k, v_{x_k}, v_{y_k})$, $\varepsilon_k = (\frac{a_{x_k}T^2}{2}, \frac{a_{y_k}T^2}{2}, a_{x_k}T, a_{y_k}T)$, (x_k, y_k) is the coordinate of the mobile terminal at k-th time, (v_{x_k}, v_{y_k}) is the velocity of the mobile terminal at k-th time , (a_{x_k}, a_{y_k}) is the acceleration distributed as $N(0, \sigma_a^2)$ and the G is

$$G = \begin{pmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}.$$

Observation Model.

In most WLAN indoor positioning algorithms, the RSS is not Gaussian so that the RSS may not be mapped into the probable location and tracking performance may be worse. So the observation model describing the relationship between the RSS and the location is presented as

$$Z_k = h_k(X_k, \phi_k) \tag{2}$$

Where $Z_k = (s_1, s_2, \cdots, s_n)$ is the observed RSS vector and ϕ_k is the observation noise distribute as $N(0, \sigma_b^2)$.

Indoor Tracking Algorithm Based on Particle Filter

Particle filter makes the combination between both observation and prediction and makes use of the sequential importance sampling (SIS) procedures, where the importance distribution is selected as

$$Q(x_{0:k} \mid z_{1:k}) = Q(x_{0:k-1} \mid z_{1:k-1}) Q(x_k \mid x_{0:k-1}, z_{1:k}) \tag{3}$$

The posterior probability could be presented as

$$p(x_k \mid z_{1:k}) = \sum_{i=1}^{N} w_k^i \delta(x_k - x_k^i) \tag{4}$$

Where w_k^i is updated by

$$w_k^i = w_{k-1}^i \frac{p(z_k \mid x_k^i) p(x_k^i \mid x_{k-1}^i)}{Q(x_k^i \mid x_{k-1}^i, z_k)} \tag{5}$$

Then the state vector X_k could be estimated as

$$\hat{X}_k = \sum_{i=1}^{N} w_k^i X_k^i \qquad (6)$$

So the tracking algorithm based on particle filter can be described as follows.

Step 1: Initialization

It is assumed that the initial position of mobile terminal is known as $X_0 = (x_0, y_0)$. In the positioning area, particles are evenly scattered and each particle represents the possible location of the mobile terminal. So the initial state is set as $x_0^i \sim p(x_0), w_0 = \frac{1}{N}, i = 1, \cdots, N$, where $p(x_0)$ is a known prior distribution and N is the number of particles.

Step 2: Particle Sampling

When the mobile terminal moves from time k-1 to time k, the particles also spread at the same time. With the sequential importance distribution (3), the current state is sampled,

$x_k^i \sim Q(x_k \mid x_{k-1}^i, z_k), i = 1, \cdots, N$

Step 3: Calculation of the weight and normalization

According to (5), the weight w_k^i is calculated and normalized as $\tilde{w}_k^i = \frac{w_k^i}{\sum_{i=1}^{N} w_k^i}$.

Step 4: State estimation

The optimal solution is estimated by the particles at time k, $\hat{x}_k = \sum_{i=1}^{N} w_k^i x_k^i$

Step 5: Re-sampling

Particles are re-sampled by the probability $v_i = \tilde{w}_k^i$. The particles of small weight are removed. In order to maintain a balance of the number of particles, the normalized weight turns to $\tilde{w}_k^i = \frac{w_k^i a_i}{\sum_{i=1}^{N} w_k^i}$, where a_i is the re-sampling number of the corresponding particle x_i.

Step 6: Artificial Immunization

The diversity of particles must be lost because of multiple re-sampling. So the artificial immune method exactly solves that problem. In that method, the particles with high weight are increased and varied. That is to say the re-sampling particles are varied with Gaussian mutation. The variation formula is $x_i^m = x_i^a + \varepsilon n$, where x_i^m is the particle after mutation, x_i^a is the re-sampling particle , ε is the variable coefficient of $\varepsilon = \frac{\sigma}{w_k^i}$ and n is a Gaussian variable with the mean of 0 and the variance of 1.

Step 7: Do that k = k + 1 and return to the step 2.

Experiment Results Analysis

To evaluate the performance of particle filter algorithm compared to Kalman filter algorithm, a laboratory is selected to carry out the experiment as in Figure 1. In the indoor environment, the rectangular area of 50m * 40m is equally divided into 50 * 40 small regions and four APs are deployed.

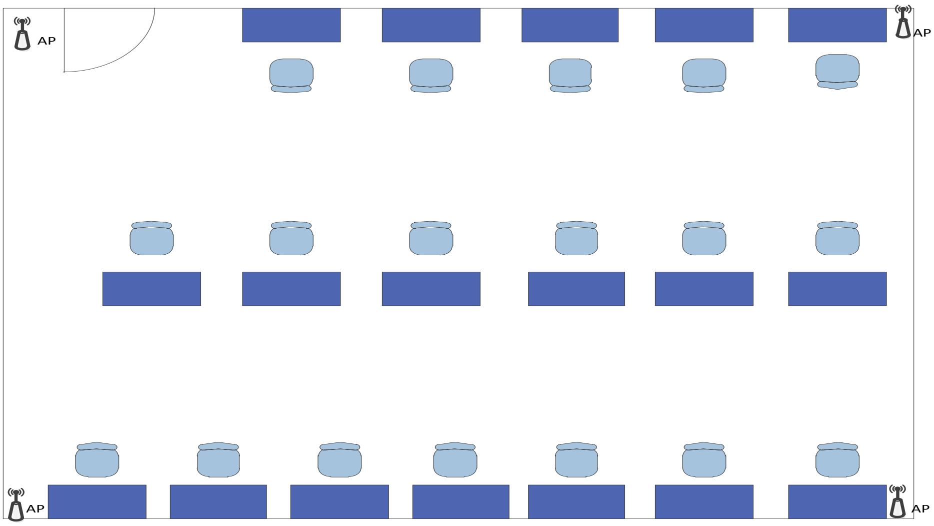

Figure 1 Indoor environment

In the offline phase, a fingerprint database is established according to the RSSI from 4 APs at each reference point and the RSS is distributed as (2). In the online phase, the Android phone gets real time data to do positioning work and (3) is normally selected as $p(x_k \mid x_{k-1})$. We selected the walking trajectory as diagonal line and set the walking velocity as v=1m/s. (see Figure 2)

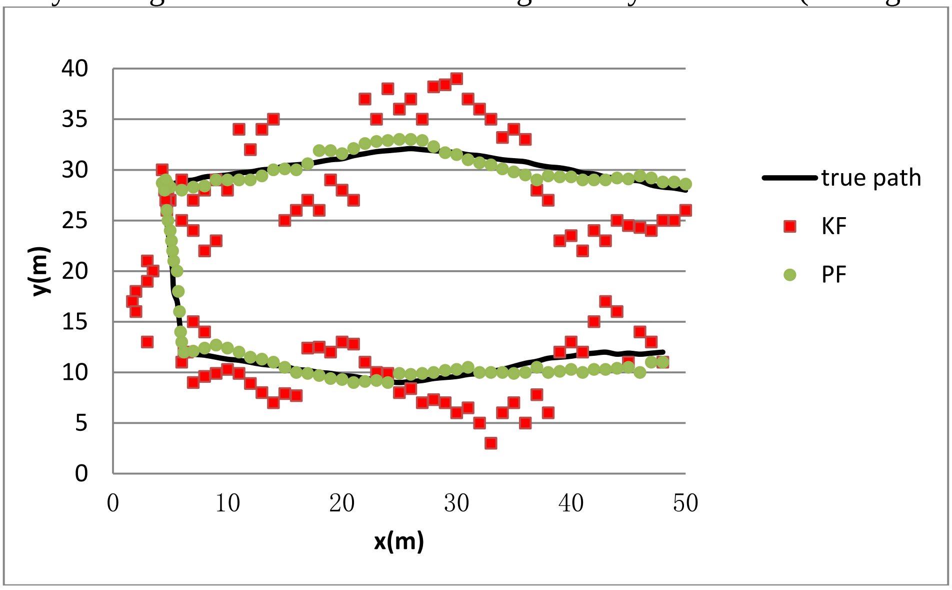

Figure 2 Trajectory comparison

It is apparent that it performs better with the particle filter. And the comparison of tracking performance is shown in Table 1.

Table 1 Positioning error on different positioning technologies

Positioning technology	Standard deviation of distance
KF	3.23
PF	2.14

This paper also mentions the artificial immunization, where ε is selected to be a proper value, because Low value of ε may lead to the lack of particle diversity. In contrast, the particles are eliminated due to low weights. So we choose different values of ε to conduct the environment. Supposed that the system noise σ_v =3, the result is shown in Table 2.

Table 2 Error on different variation coefficients

$\sigma = \varepsilon w_k^i$	σ_v	$2\sigma_v$	$3\sigma_v$	$4\sigma_v$
Standard deviation of distance	3.89	3.32	3.41	4.12

In this paper, the tracking accuracy based on particle filter is also dependent on the number of particles. Therefore, experiments are made when the number of particles is taken from 300 to 700 at the interval of 100. The result is shown in Table 3 and it is obvious that it has a better positioning performance when the number of particles is 600.

Table 3 Error on different number of particles

The number of particles	300	400	500	600	700
Standard deviation of distance	3.14	3.03	2.18	2.09	3.05

Conclusion

In this paper, the indoor tracking system based on particle filter with a proper variation coefficient has a more precise positioning performance than the previous positioning systems based on Kalman filter. In addition, the selection of the particles number in particle filter also has an important influence on the tracking. The experiment shows that positioning accuracy is greatly improved when the number of particles is 600, even though a little timeliness is reduced. In conclusion, our algorithm achieves great accuracy and robustness in tracking trajectory aspect and performs better than the tracking algorithm using Kalman filter.

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