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Enhancing the Accuracy of Indoor Positioning Using System Delay Time Compensation

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Abstract

Indoor positioning based on the Hidden Markov Model (HMM), which utilizes a combination of Received Signal Strength Indicator (RSSI) from Access Points (APs) and inertial sensors, has been exploited broadly due to its superiority compared to other approaches. Some previous studies, which have utilized a combination of two methods, have often assumed the users do not move in the system estimated time and normally this time has been neglected. However, when the number of reference points is huge, and the user moves a considerable distance, the computational time of the system increases considerably. In this case, the system computational time cannot be cancelled. This paper presents an approach to improving the accuracy of the positioning system. By considering the processing time of the system when it estimated the position of the user, and then cooperating the measured information from the inertial sensor, the localization of the user is estimated more accurately. The simulation results show that the proposed approach achieves a remarkable effect compared to previous studies with the same scenario even if the user moves or does not move in a large area.

Keywords

Indoor localization,

Hidden Markov Model,

Delay time compensation,

Inertial sensors.

1. Introduction

In the past decade, the indoor positioning system has been particularly interested by researchers because of its widespread application in our life. This system can be applied in many areas such as navigation positioning, asset management, disaster management, tracking security and recovery, contextual aware location-based marketing, and customer, assistance health services [1,2]... For the outdoor environment, the Global Positioning System (GPS) has achieved great success. However, indoor transmission environment has featured as many obstructions, obscured vision, affected by multi-path effects so that the techniques applied to outdoor systems are not suitable for inside buildings. There is no standard solution for indoor positioning technologies that can satisfy the actual requirements like Global Navigation Satellite Systems (GNSS). Therefore, the challenges posed to indoor positioning are always issues that needed to be solved. In [1-2], the Indoor Positioning System (IPS) is now divided into three research directions: (i) localization system which bases on signal strength obtained from networks such as Wi- Fi , Bluetooth, wireless sensor network, Ultra Wide Band network; (ii) positioning system which relies on the inertial sensor integrated on a handheld device; and (iii) the hybrid system which incorporates many positioning methods. In [1], many previous studies have shown that the techniques used in indoor positioning tend to be chosen based on RSSI because of its due to the advantages of this method are as follows: it is easy to be implemented, the cost is quite low, no more additional hardware is needed [3-6].

However, this method has some disadvantages such as the signal is attenuated due to transmission in the indoor environment, it is easily affected by the multi-path environment and a complicated transmission model must be built These studies belong to the first research direction, and Fingerprinting based method is the most popular. This method produces the estimated position of a user relying on training data from a set of reference points (Anchor Points) with known locations. In the offline training phase, it proceeds to collect signals from different positions and create a database called a radio map. In the classification positioning phase, the estimated position is computed by finding the best match between the classifications measured data and the training data. In addition to the well-known RSSI fingerprinting-based technique, Dead-Reckoning is another method working by collecting signals from the inertial sensors to calculate the moving distance and direction of the mobile user [8]. In [9-10], they have used an accelerometer sensor to calculate the movement distance and the transition probability of the HMMs. In the past, this method had some limitations due to the requirements of integrating additional hardware such as acceleration and gyroscope sensors. However, it is becoming widely used because of its advantages: (i) electronic circuit technology is developing rapidly, smartphones usually have built-in inertial sensors so that signal collecting from the sensors is made easily, thus the cost of implementation is also greatly reduced; (ii) this method provides very high positioning accuracy if we perform positioning in the narrow range and a short distance of moving users. However, accumulated errors are the main drawback of this positioning method.

Recently, many researchers have been using a combination of the techniques mentioned above taking their advantages and eliminating their drawbacks for positioning estimation. These hybrid methods show their superiority compared to individual methods. Both PDR and Wi- Fi Localization systems are the two most common techniques and have limitations as well as advantages when they are used individually in navigation systems. Combining both systems will exploit all of their individual advantages. Tell the detailed way, the PDR method enhances the accuracy of Wi- Fi localization, while Wi- Fi based localization is useful for adjusting the cumulative PDR drift errors. In this paper, the method of combining two of those techniques is selected. HMM is used to combine the receiver signals from sources (APs and inertial sensors). The system needs a period to estimate the user location. This position estimation time depends on two factors: the first factor is the time that HMM needs or requires executing the maximum likelihood algorithm; the second factor is the time to calculate the distance and direction of motion based on inertial sensors. However, the localization calculation time depends mainly on the first factor because when the number of reference points in fingerprint technology is very large, the time that HMM needs to estimate the user position in the classification phase will increase significantly. Opposite to this time, the time to determine the direction and distance of the movement of the user based on inertial sensors is very small and can be ignored. In previous studies, it was often assumed that the time to estimate the position was small enough to be ignored and considered as the user does not move during the calculation. However, when the number of reference points in the fingerprint technique is huge, this computation time cannot be ignored. Furthermore, the user is not always stationary but also moves a considerable distance during that time. Therefore, any previous assumptions are not correct when the user moves a distance and the localization estimated time is large. In this paper, the position result is determined by the distance that the user moves during the system's estimation time (based on inertial sensors) and the position of the user which is given by HMM. The simulation results show a remarkable improvement in positioning accuracy compared to previous research methods in the same scenario.

The rest of the paper is organized as follows: In section 2 material and methods are presented. In section 3, we present the simulation results and give some discussions. Finally, the paper is summarized in the conclusion section.

2. Material and Methods

In this section, we present the principle of estimating the location that uses HMM model combines the pedestrian motion model, Wi- Fi signals, and building maps. The Wi- Fi -based positioning technique is mostly the fingerprinting method. The fingerprinting method includes two phases, the training phase, and the classification phase. The RSSI values of the placements collected during the training period were labeled corresponding to the known positions. In the classification phase, the RSSI of the WLAN access points is compared with the access points from the training phase. Therefore, based on the comparison of the RSSI value of the most suitable classification phase with the value measured during the training period, the position of the subject will be estimated. The map data distribution has described in the section 2.1. The proposal system for online localization procedure has presented in section 2.2, and the proposal algorithm has presented in 2.3.

2.1. The map data distribution

In the fingerprinting method, the positioning accuracy depends highly on how well the models are trained, how accurate the training parameters and how dense the positions with training data are. In this section, we present parameter estimation of RSSI model in the training phase. Obviously, if we collect training data for a dense grid of positions, the performance of fingerprinting based positioning techniques is better. In [5], the authors proposed to Expectation Maximization (EM) algorithm to estimate the parameters that were following Gaussian distribution when the data is incomplete. The pseudo-states were inserted as the reference points between APs to decreasing the time in the training phase and to increasing the performance of the positioning system. However, it is very time-consuming to develop an indoor positioning system for a large area [5]. Even when using the method of inserting pseudo-states to reduce training time, it takes considerable time to estimate the position of the user in a large area. Therefore, the parameters affect the accuracy of the system such as the number of reference points; time to estimate the position; distance that the user can move during the time the system performs the estimation task... we fully cover in this article. The firstly, we construct the map data distribution for the system in this section.

Let $x_i'\left(i=1,2,..M\right)$, (M is the number of Base Station – BS) be the set of observed signals and x_i' follow the Gaussian distribution $N(m,\sigma^2)$ where m is the mean and σ^2 is the variance, k is the clipping threshold value. If RSSI at the APs is less than value k, the receiver will not be able to receive the signal. According to [5] we have:

$$x_i=\max(x_i',k)=\begin{cases} x_i' & z_i=0 \\ k & z_i=1 \end{cases} \tag{1}$$

In which x_i is the completed data set, z_i is a binary variable that takes either 0 or 1, $z_i=1$ when it detects that the signal is clipping, $z_i=0$ when the signal is fully received. In [6], to determine the user's location l_s we calculate the likelihood of an observation vector $x=\left(x_1...x_{N_{AP}}\right)^T$ (N_{AP} is the number of Wi- Fi Access points) in the classification phase and compare with RSSI values of Wi- Fi Access points in the training phase. In the case of data is censored this calculation is done according to (2):

$$p\left(x|l_s\right)=\prod_{j=1}^{N_{AP}} p\left(x_i|l_s\right) \tag{2}$$

Then, assume at position l_s the estimated parameters of the i-th AP are respectively $\left(m'_{l_k,j},\sigma'^2_{l_s,i}\right)$ then $p\left(x_i|l_s\right)$ is calculated as follows:

$$p\left(x_i|l_s\right)=\begin{cases} \mathrm{N}\left(x_i;m'_{l_k,j},\sigma'^2_{l_s,i}\right), & if\ \ x_i>k \\ I_0\left(m'_{l_k,j},\sigma'^2_{l_s,i}\right), & if\ \ x_i=k \end{cases} \tag{3}$$

The assumptions about $\left(m'_{l_k,j},\sigma'^2_{l_s,i}\right)$ and k follow scenario in [6].

2.2. Proposed system diagram for online localization procedure

Figure 1 shows the system diagram which illustrates our proposal. In this diagram, two types of signal are taken by a smartphone such as Wi- Fi RSSI and inertial data. The signals observed during the online phase from two sources will be processed and fed into the HMM to estimate user location. Each hidden state of the HMM is a reference point in the radio map. According to the proposed algorithm, there are two stages for estimating the user position: in the first stage, HMM is utilized to fuse inertial data and Wi- Fi RSSI to determine the user position (x', y') and in the second stage, during the time Δt which was needed for computing the user position, the user might keep moving with a movement vector of Δs (Δs including distance and direction. If the user does not move, Δs is considered equal to zero). The measurements of the inertial sensor during Δt were used to compute the Δs. The final user location estimate (x, y) was obtained by combining the above two stages.

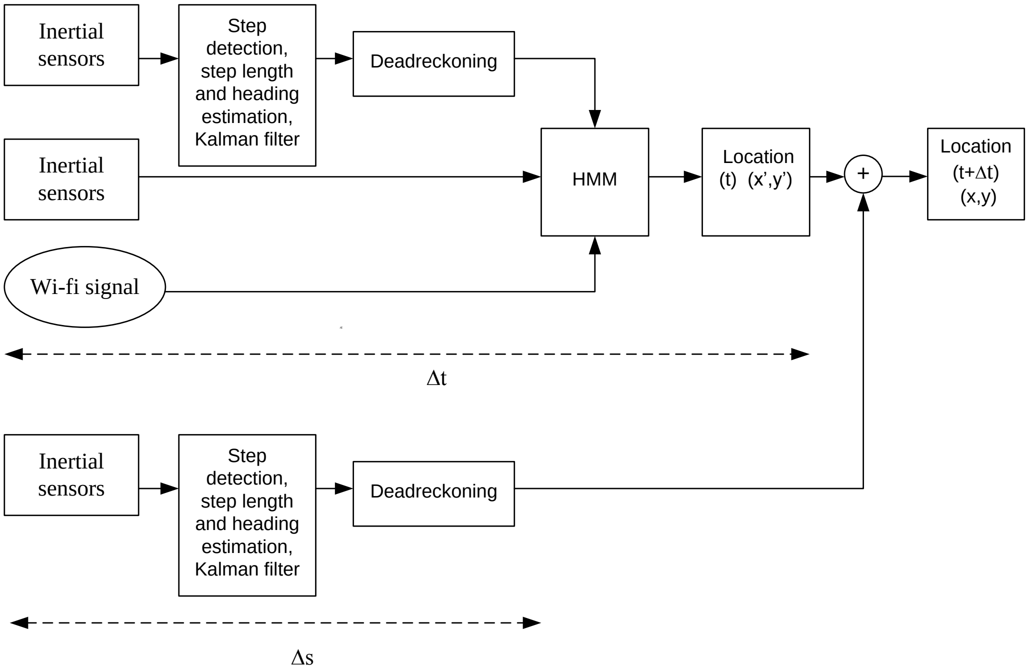

Figure 1: Proposed system diagram

2.2.1. Moving direction and distance estimation

In [7], the 3-dimensional acceleration vector from the accelerometer is used to detect steps. By using a low-pass filter to reduce sensor errors and detect steps by counting the number of times the signal surpasses a specified threshold. A rotation matrix R is calculated by using the magnetometer data and gravity information. And then Kalman filter is used to obtain a yaw angle by combining the two information sources. V_t is a movement vector. The Probability Density Function (PDF) of movement vector is assumed to follow the Gaussian distribution and calculated as equation (4):

$$\alpha_t(k) = \sum_i p(v_t \mid s_{t-1} = i).p(\mathrm{x}_t \mid s_t = k)$$
$$.\,\mathrm{P}(\mathrm{s}_t \mid s_{t-1} = i).p(\mathrm{s}_{t-1} = \mathrm{i}, \mathrm{v}_{1:t-1,}\, x_{1:t-1}) \quad (4)$$

where $m_{k,\mathrm{h}} = l_k - l_h$ is a mean vector, $\sum_v$ is a predetermined diagonal covariance matrix, , l_k, l_h are two- dimension position vectors corresponding to k-th, h-th states.

2.2.2. Hidden Markov Model – HMM

A Hidden Markov Model is a statistical model in which the system is modelled to be a Markov process with unknown parameters. The task of this model is to identify unknown parameters from the observed parameters. For indoor positioning purposes, the hidden parameters in the model are considered the position of the user. In order to estimate the position of the user, the Forward algorithm is used [7]. Specifically, in the positioning problem, when there is Wi- Fi data in the classification phase, it will calculate the suitable probability between the received data and the data in the offline phase to determine the location of the user.

$$\alpha_t(k) = \sum_i p(v_t \mid s_{t-1} = i).p(\mathrm{x}_t \mid s_t = k)$$
$$.\,\mathrm{P}(\mathrm{s}_t \mid s_{t-1} = i).p(\mathrm{s}_{t-1} = \mathrm{i}, \mathrm{v}_{1:t-1,}\, x_{1:t-1}) \quad (5)$$

$\alpha_t(k)$ is the probability of being at time t in k state, while having observed the sequence of $x_{1:t}$ ($x_{1:t} = [x_1 : \mathrm{x}_t]$ were the sequence of RSSI measurements up to time t) and the step detection information is gathered in the sequence $v_{1:t} = [v_1 : v_t]$. Equation (5) shows how the different knowledge sources are combined. s_t indicates the variable value of the hidden states obtained at time t . In (5), the term $p(\mathrm{x}_t \mid \mathrm{s}_t = k)$ is the likelihood of the RSSI measurement x_t . When k is huge, the number of reference points is large; the time needed to execute Forward algorithm is longer. This is a cause for making the position estimation time of the system increase.

2.3. The proposal algorithm

In this section we have presented the proposal algorithm.

Input: seconds per sample, number of samples

Maximum speed of user, increase in case of Ursain Bolt

Basic Simulation time base

Maximum distance between nodes

Insert node if distance is larger

Number of base stations

Number of simulated time instances

Output: Compute true positions after computation time; Find the closest Node to the estimate position

Calculate error MSE.

- Generate acceleration data, parameter definitions
- Compute velocity from accelerometer data.
- Compute displacement from velocity data.
- Compute displacement after each one second.
- Create Basic Graph.
- Enhance graph by introducing pseudo nodes.
- Compute true positions after computation time of the HMM algorithm.
- Find the closest node to the estimate position.
- Calculate error MSE

3. Numerical results

In this section, we have used MATLAB to simulate scenarios to evaluate the effectiveness of the proposed positioning method compared to the previous studies in [5-6]. The paper uses the parameters initialized according to [5-6]. The floor plan of the area in our simulation scenario has illustrated in Figure 2, in which the survey area is 50m x 45m. The number of Base Station (BS) is 20 (B1 - B20); the location of BS is randomly regenerated after each simulation run. The number of reference points in this scenario is 200; the solid lines on the floor plan tell us the path that the user can move. The simulation time (HMM processes every time base seconds) is 1.5 s. The user's highest travel speed is 3 m/s, the sensitivity limit is 100 dBm (lower threshold of observable RSSI) [5]. Figure 3 shows the cumulative distribution functions of positioning errors.

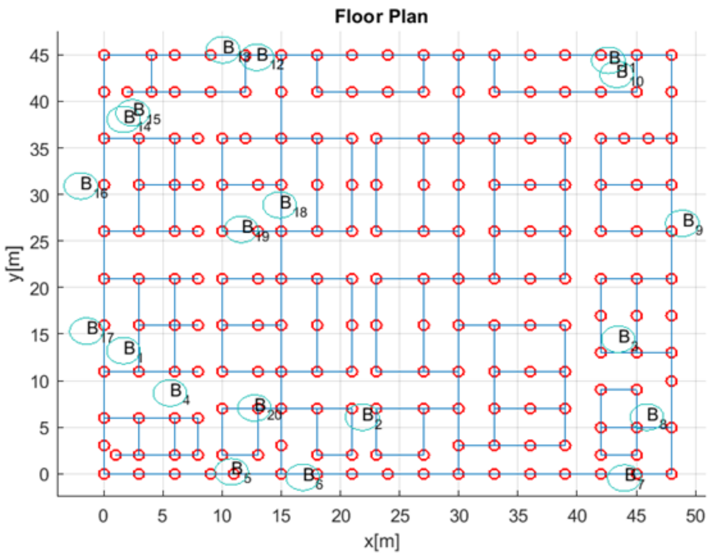

Figure 2: The floor plan of the area in simulation scenario

Those curves on the figure 3 describe the probability which the positioning error is less than a certain distance as described in eq. (6).

$$CDF_e\left(d\right) = P(e \leq d) \qquad \mathrm{d} \geq 0 \tag{6}$$

In case of errors in positioning required less than 1m accuracy, the probability of achieving very low, especially for the proposed method in ICASSP [5] is only 20% and slightly better with the proposed method in EUSIPCO[6] is 35%, while our proposed method achieves more than 60% efficiency. When the error is about 2m, the proposed method achieves a probability of about 80% compared to 70% and 40% of EUSIPCO and ICASSP, respectively. The results show that the outstanding accuracy in user positioning of the proposed method compared to the previous research results.

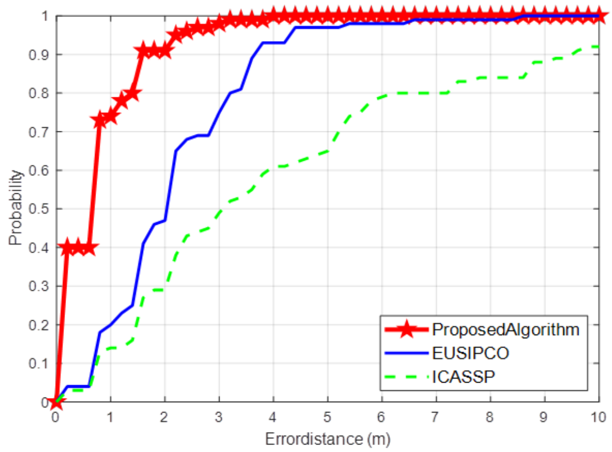

Figure 3: CDF of the positioning error for EUSIPCO and ICASSP systems

4. Conclusion

In this paper, the system's delay time compensation has been proposed for enhancing the accuracy of indoor positioning. Noted that the processing time of the HMM highly depends on the computation of the emission probabilities which directly relates to the number of RPs and the number of APs in the deployment area. In this case, the number of reference points in fingerprinting is dense and the survey area is very large, the proposed approach has achieved a remarkable effect even the objects move or do not move. The results show that the proposed approach can be used in the indoor positioning system, which requires real-time. Furthermore, compared to some previous methods, our recommendation is more accurate in terms of accuracy when estimating user location in a large range. On the other hand, inserting pseudo nodes does not much cost in the training phase.

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Author'sBiography

Ms. Hang Duong Thi was born in Bac Giang, Vietnam, in 1978. She has been a lecturer at the Faculty of Electronic Engineering, Hanoi University of Industry since 2000. She received the B.S and M.S degree from VNU University of Engineering and Technology, in 2000 and in 2005, respectively. She is currently pursuing the Ph.D. degree in telecommunication engineering at VNU. Her main research interests are in indoor positioning systems, machine learning, and pattern classification, nature-inspired algorithm application.

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