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Extended Kalman Filter for wireless LAN based indoor positioning

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ABSTRACT

A WLAN (Wireless Local Area Network) based Extended Kalman Filter (EKF) method for indoor positioning is introduced in this paper. WLAN based indoor positioning is more economical than other methods because it does not require any special equipment dedicated to positioning. The most popular technique used for indoor positioning is the fingerprinting method, but the EKF method is easier to deploy because, unlike fingerprinting, it does not require a time consuming off-line phase. This paper also provides experimental comparisons of our EKF method with other indoor positioning methods.

1. Introduction

The location based services (LBS) provided in the ubiquitous environment require the accurate positions of the users and, as a result, positioning techniques have become one of the most important elements in ubiquitous networks [7]. The Global Positioning System (GPS) is the most representative method of positioning and is widely used in practical outdoor LBS systems. However, GPS cannot be utilized indoors because the GPS signal cannot be received if line of sight visibility to the satellites is lost.

In order to make indoor LBS possible, many indoor positioning techniques have been developed recently. Active Badge [28], which involves positioning by sensing infrared signal, Active Bat [10] and Cricket [22], which involve positioning by using the difference between the propagation times of ultrasound and RF signals, and RADAR [3], which involves positioning by using the strength of the received UDP signal, are among the most representative indoor positioning systems. These systems are highly accurate, but they also have their own shortcomings. That is, they require special equipment dedicated to positioning.

Many indoor positioning systems which do not require special equipment have also been developed. Most of them use RF-based WLAN (wireless LAN) positioning techniques. Nowadays, WLAN is available in many places including in college campuses, airports, hotels and even homes. The indoor positioning system we introduce in this paper is also a kind of RF-based WLAN positioning system. An RF-based WLAN positioning system determines a user's position by referring to the received signal strengths (RSSs) of the signals from various access points (AP). The most popular method used to determine the user's position is the fingerprinting method [2,3,12–14,17,18,27,30,31]. In implementation of fingerprinting method, we can apply any classification or decision making techniques such as the ones shown in [1,21,24,25].

The deployment of fingerprinting based positioning systems consists of two phases. First, in the off-line phase, the location fingerprints are collected by performing a site-survey of the RSSs from multiple APs. The vector of the RSS values at a point is called the location fingerprint of that point. The second phase, the on-line phase, gathers the RSSs the

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user receives at the present moment and matches them with these fingerprints to determine the user's location.

It is known that the fingerprinting method is fairly accurate. However, it has a serious shortcoming. That is, the off-line phase is extremely time consuming. An alternative choice is the RF propagation loss model based method [9,16]. The RF propagation loss model is a simple mathematical expression representing the relationship between the RSS and the distance between the sender and the receiver. However, the RSS is influenced by many parameters and establishing an appropriate RF propagation loss model is very difficult. As a result, the RF propagation loss model based positioning method is less accurate than the fingerprinting positioning method. Nevertheless, we propose an RF propagation loss model based WLAN positioning method in order to avoid the time consuming off-line phase process.

A mobile terminal, in an RF-based WLAN positioning system, measures the strengths of the signals received from at least three different fixed position stations. Then, by applying an RF propagation loss model to these signal strengths, the mobile terminal estimates its distances from the stations. By applying trilateration to the distances and the coordinates of the stations, the mobile terminal can estimate its position. The variance of the indoor positions estimated by trilateration is usually quite large, because of the noise in the RF signal. To obtain a more accurate position from noisy distance measurements, the terminal repeats the estimation process a number of times and determines its position to be the average of the estimations.

Trilateration is a kinematic method which does not consider the user dynamics, while the Kalman Filter [6,8,15,19] is applicable to a dynamic system. The Kalman Filter estimates the state of a process by iteratively predicting its state and adjusting the prediction with measurements. One of the characteristics of the Kalman Filter is that it minimizes the mean of the squared error. There are hundreds of papers on the Kalman Filter, most of which involve its application to autonomous or assisted navigation [4,5,20,26], whereas there have been few reports on its application to indoor positioning or navigation.

Kotanen et al. [15] and Qasem et al. [23] used the Kalman Filter for indoor positioning. However, they used special equipments such as Bluetooth antennas [15] or radar transponders [23]. On the other hand, our experimental environment is a WLAN. WLANs are installed in most buildings, nowadays, due to the prevalence of mobile computing. Therefore, our Kalman Filter method can be easily and economically applied in practical use.

2. Related works

This paper introduces a WLAN-based indoor positioning method using the Kalman Filter. Therefore, WLAN-based indoor positioning techniques are summarized in this section. They can be classified into fingerprinting methods or RF propagation loss model based methods.

Table 1
An example look-up table of K-NN (CP_i are the coordinates of the i-th candidate points, and AP_i is the MAC address of the i-th AP)

	AP_1	AP_2	AP_3	AP_4	AP_5
CP_1	−39	−55	−56	−70	−67
CP_2	−40	−56	−55	−69	−66
CP_3	−44	−42	−62	−45	−61
…	…	…	…	…	…

Table 2
Example training data tuples (CP_i are the coordinates of the i-th candidate point, AP_i is the MAC address of the i-th AP, and I stands for interval)

	AP_1	AP_2	AP_3	AP_4	AP_5
CP_1	I_2	I_1	I_2	I_5	I_5
	I_1	I_1	I_2	I_1	I_1
	…				
CP_2	I_3	I_2	I_3	I_1	I_2
	…				
…	…				

2.1. Fingerprinting methods

The K-NN (K Nearest Neighbors) [3], Bayesian [11,18] and decision tree [2,29] methods are representative techniques used in fingerprinting positioning and they are briefly summarized in this section.

2.1.1. K-nearest neighbors

In K-NN, we build a look-up table in the first phase, or off-line phase. The entire area is covered by a rectangular grid of points called *candidate points*. At each of these candidate points, we measure the RSSIs many times. Let $RSSI_{ij}$ denote the j-th received signal strength indicator of the signal sent by AP_i. A row of the look-up table is an ordered pair of (coordinate, a list of RSSIs). A coordinate is an ordered pair of integers (x, y) representing the coordinates of a candidate point. A list of RSSIs consists of five integers, $RSSI_1$, $RSSI_2$ …, where $RSSI_i$ is the average of $RSSI_{ij}$ received at (x, y) and sent by AP_i. An example of a look-up table is shown in Table 1.

In the second phase, or on-line phase, the positioning program gathers the RSSIs the user receives at the current moment. If the positioning program is running on the user's handheld terminal, then the terminal itself will collect the RSSIs. For example, let $X=(-40, -56, -54, -69, -66)$ be the vector of the collected RSSIs. K-NN, then examines the look-up table and finds the closest candidate point, CP_2 in the case of Table 1, and returns it as the user's current location. If K equals 2, then it will find the two closest candidate points and return the average of their coordinates as the user's current location.

2.1.2. Bayesian classification method

Let $X=(x_1,x_2,\ldots,x_n)$ be the vector of collected RSSIs. The positioning program will predict that the user's position is CP_i if $P(CP_i|X)>P(CP_j|X)$ for $1 \le j \le m$, $j \ne i$, where, m is the number of candidate points. According to Bayes' theorem, $P(CP_i|X) = \frac{P(X|CP_i)P(CP_i)}{P(X)}$. As $P(X)$ is constant for all classes, only $P(X|CP_i)P(CP_i)$ need be maximized. A positioning system using the Bayesian classification method finds the CP_i that maximizes $P(X|CP_i)P(CP_i)$, and returns it as the user's position [27].

2.1.3. Decision tree

In the off-line phase of the decision tree method [29], we build a decision tree with the training data. An example training data set is shown in Table 2. Table 2 is similar to