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IEEE 802.11 WLAN Based Real Time Indoor Positioning: Literature Survey and Experimental Investigations

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Abstract

Indoor positioning has emerged as a hot topic that gained gradual interest from both academia and industry. Accurate estimation is necessitated in a variety of location-based services such as healthcare, repository tracking, and security. Additional equipment for location sensing could be used for accurate estimation, but they are not widely used in general because those alternatives will cause specialization in brands and will be costly. Among all suggestions in literature including hardware and intense sophisticated computations, a versatile and low-cost location determination technology, which uses existing WLAN infrastructure of indoor environments, has been developed without incurring extra charge; this method is rising as a way of positioning. WLAN is capable to be used within an indoor positioning system soon in real environments. It is a good alternative in terms of accuracy, precision and cost, compared to similar systems. Especially with the common usage of smartphones and tablet PCs, it became the most easy-to-use method, too. In this paper, we present a brief survey on such systems, methodologies, techniques and discuss advantages and disadvantages of each of these.

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Keywords: Indoor Communication; Wireless LAN; Location-aware systems; Indoor Localization;

1. Introduction

Nowadays, localization of people and mobile devices has started to be used in various applications and systems, which is creating a trend appealing to industry and academics at the same time. Provided that an accurate estimation is made for location sensing, it could lead to substantial context-aware computing systems and location-based services like navigation, object finding, and content delivery[1].

Global Positioning System (GPS) is obviously the most widely used outdoor location sensing technology, but there are several drawbacks which make GPS impossible to be used as an indoor positioning system. Due to line-of-sight demand between the satellites and the receiver, and specialized hardware requirement, it has poor indoor coverage and insufficient accuracy[2]. Additionally, interference and noise sources within the environment affect GPS accuracy[3].

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There are several technologies that were developed for only indoor localization purposes. However, currently, they are not commonly used due to their cost and performance. If a low-cost and relatively high-performance location determination technology is developed, it has the potential to be used widely and it can become a popular way of localization[4]. Compared to the other indoor positioning techniques, wireless systems are easier and cheaper taking into account that many buildings and structures have an existing WLAN infrastructure. Since GPS cannot be used for positioning in indoor environments, GPS can be unified with an indoor location system, so that localization systems can prove more useful and beneficial. Therefore, the integration of GPS into today's wireless technology is regarded as a key complement to location-aware systems[5].

The organization of this paper is as following. First, Section 2 begins introducing wireless localization techniques and 3 explains common approaches. Next, Section 4 points out the performance metrics of such systems. While Section 5 experiments with real world data Section 6 finally concludes.

2. Wireless Localization Techniques

There are very serious research efforts on indoor positioning but the developed systems aren't widely used yet. Some of the main reasons are, these systems are either too expensive or not adequately accurate or both at the same time. Some common methodologies developed over years are given below.

Angle of Arrival (AoA): This methodology is mostly suitable for areas that there is a direct line of sight between mobile user (MU) and reference points (RP). Location is calculated by measuring the angle between a line that runs from the RP to the MU and a line from the RP with a predefined direction[6]. While providing very accurate and precise results within areas where direct line of sight can be sustained, the biggest drawback of this methodology is the need of special RPs that can sense the exact direction of the received signal.

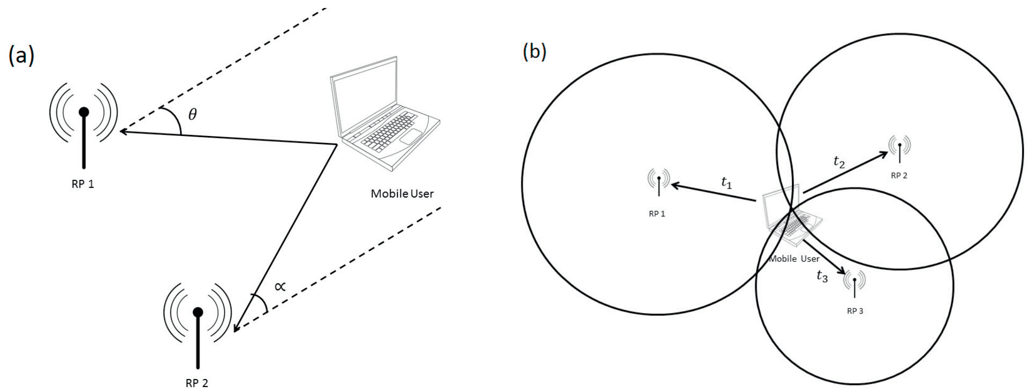

Fig. 1. (a) Angle of Arrival and (b) Time of Arrival

Time of Arrival (ToA): This methodology is based on the measurement of the amount of time required for a signal to travel from a MU to one or more RPs. This amount of time is named propagation delay and the distance between a MU and a RP can be determined by this method. This operation is considerably difficult to perform accurately and also, the clocks of the MU and the RP must be synchronized in order to measure the time.[6].

Time Difference of Arrival (TDOA): This method measures the difference in transmission times between signals received from each of the RPs to a user. It is very similar to ToA but ToA records the time of the user sending a signal to the RP, and it is required that the RPs record when the signals were received in TDoA. Like ToA, TDoA also requires that each signal to be transmitted synchronously and like ToA, TDoA requires the clocks of each of the RPs to be synchronized. Furthermore, TDoA is also affected by multipath propagation, noise and interferences. Therefore, direct line of site is preferable, such as in open space or in large open buildings[6].

Time of Flight (ToF): This method uses measured elapsed time for a transmission between a user and a RP. As this method is based on a time value, clock accuracy becomes significantly more important than in previous methods. Therefore, ToF system requires costly accurate and sharply synchronized clocks[6].

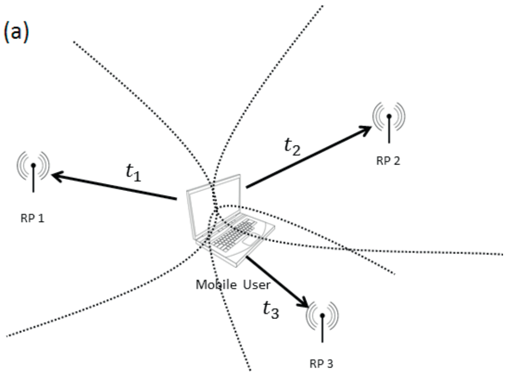

Fig. 2. (a) Time Difference of Arrival and (b) Time of Flight

These approaches mostly require extra equipment which highly increases the cost for such a system. Usage of IEEE 802.11 Wireless local area networks in indoor positioning systems have become an important alternative. WLAN cannot be considered as a direct way of positioning due to its design and purpose. Nonetheless, some properties and characteristics of WLAN signals can be used to calculate the position of an asset. The most common indicator is signal strength (SS) of the signal received from an access point (AP) and there are several SS based techniques that have been proposed for position estimation in environments in which WLAN is deployed[15].

3. Localization Methods Using WLAN

With the increasing capabilities of wireless technology and the current processor power of even simple tablet PCs, it is possible to localize people and objects remotely, within a predefined time frame more accurately than before. Received Signal Strength Indication (RSSI) is an indoor localization methodology based on WLAN. Although the RSSI data provides a complex and unsteady dataset because of multi-path propagation in sophisticated indoor areas and it isnt intended to be used as location sensor[7], it is still enough to calculate the position of a given asset. Furthermore, the RSSI based systems don't need any additional hardware to the existing Wireless LAN infrastructure.

Moreover, granularity, RF measurement accuracy and range for actual power in dBm of mobile devices and APs depend on the vendor and these devices have different pros and cons and the mapping between actual RF energy and range of RSSI values is different for each vendor. As a result of this phenomenon, different WLAN cards arent equal[7].

There is no relationship that is defined in IEEE 801.11 standard between RSSI value and power level in mW or dBm[8]. However, Microsoft defines that the normal range for the RSSI trigger values is from -10 through -200 dBm. The trigger value contains the RSSI measurement in units of dBm[9].

For these reasons defined above, there is no direct location calculation method universally accepted and used. Actually, the most suitable technique should be determined for each site.

Received Signal Strength based techniques can be separated into two approaches. These approaches are fingerprinting and RF propagation loss model approaches. With knowledge of the coordinates of the WLAN APs, the method of trilateration can then be used to compute the position of the MU. The other category of WLAN positioning is known as location fingerprinting. The key idea behind fingerprinting is to map location dependent parameters of measured radio signals in the area of interest .

3.1. Fingerprinting Approach

Fingerprinting approach is basically creating a map of SS vectors. Each vector belongs to the coordinate of the measurement taken in the area of interest. These vectors are used to calculate the position of a MU. One of the best advantages of this approach is that the locations of APs don't need to be known to make an estimation. Also, if one of the APs get disabled for a time, localization can still be performed.

Signal Strength is a measured value of power received from an AP at a certain time by a wireless device placed to a known or unknown location. *Signal Sample* is a set of measured values of power received from all APs within sight (no direct line of sight needed) at a certain time by a wireless device placed to a known or unknown location. Basically, it is a set of signal strengths from all APs nearby. *Fingerprint* is a collection of signal samples collected within a time period at a location known or unknown. *Signal Vector* is the vectoral representation of signal samples.

Fingerprinting approach consists of two phases: "training" and "positioning".

Training Phase: The training aims at creating a fingerprint database which includes various information about the environment, and signal data. During the database creation process, RPs have to be selected carefully. The MU should determine the strategic points, which may also be uniformly scattered around the map or the MU can do both. After that, the MU should collect the SSs of all the APs at each of these RPs. From such measurements the characteristic feature of each RP (its SS) is determined, and is then inserted into the database. The same course is redone at one other RP, and till all RPs are attained [15]. The collected data can be processed in this phase, if the positioning algorithm requires.

Positioning Phase: In the positioning phase, the location of the MU is calculated by using the RSS at a certain place. The created signal vector is processes with a fitting search/matching algorithm. The result of the algorithm shows the most probable location of the MU [15]. Positioning can be performed either online or offline. Offline positioning is usually performed for testing purposes while online positioning is performed for real time location tracking. In offline positioning, localization requires some distinct test samples apart from collected data from the testbed. The coordinates of test samples are known. The location of the test sample is calculated and then compared to the real location of the sample. Online positioning is much more complicated than offline positioning because of the real time data varies by the time. Each scan brings new wireless signal samples. The coordinates of the samples are not known. The calculation phase is executed in real time.

We can define a signal vector as

$$V_{(x,y),t} = [S_{AP_1}, S_{AP_2}, ..., S_{AP_n}] \tag{1}$$

where V is the signal vector at (x,y) location at time t, S is the signal strength from an AP.

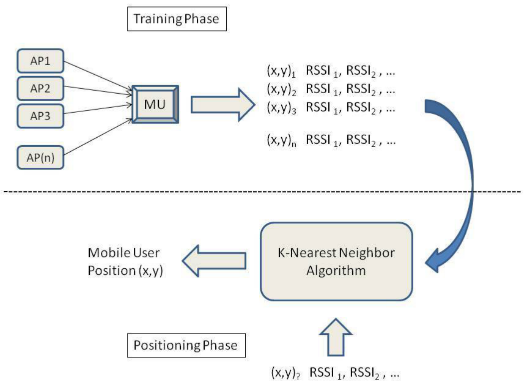

Fig. 3. Fingerprinting Approach

The K-Nearest Neighbors, decision tree, Bayesian classification and neural network methods are the most common techniques that are used in systems using fingerprinting approach owing to their simple structure.

3.1.1. K-Nearest Neighbors

This method constructs distance vectors from RSSI data and calculates the position of the MU by comparing its fingerprint vector to other vectors. After that, the signal space distances (SSD) are sorted. The K samples with the smallest SSD are chosen as the "K-Nearest Neighbors" [10].

There are many pattern classification techniques to find distance. Euclidean distance can be helpful and easy to calculate. The location associated with fingerprint which has the smallest Euclidean distance is returned as the estimation of the object location[7]. The distances between the fingerprints can be calculated with

$$L_q = (\sum_{i=1}^{n} |s_i - S_i|^q)^{\frac{1}{q}} \tag{2}$$

where L is the distance between two vectors, si is the received signal strength value, S_i is the previously collected SS value, and n is the number of APs. The q value determines the type of the distance: Manhattan Distance for q=1 and Euclidean Distance for q=2[10]. Some experiments in[11] show that although Manhattan distance is more accurate, the improvement isn't significant enough.

After obtaining the nearest-neighbor list, the fingerprint is positioned between the "k-Nearest Neighbors". In this approach, every neighbor has the same impact on the positioning. This makes the algorithm sensitive to the choice of k.

3.1.2. Bayesian Classification

This method constructs a probability distribution over the observation space in the training phase and picks the biggest probability as the position of the MU in the positioning phase[12]. In the calculation of the probability vectors, Bayesian rule can be collocated as:

$$p(l_t|o_t) = p(o_t|l_t)p(l_t)N \tag{3}$$

where l_t is a coordinate at time t, o_t is an measurement of the signals made at t. To make all probabilities sum to 1, we also define N as a normalizing factor[12].

3.1.3. Decision Tree

In this method, a decision tree is constructed with the data collected in training phase and it is used to estimate the position of the MU. The main benefit of this method is that the time needed for online positioning is lower than other methods[13].

$$I(s_1, s_2, ..., s_m) = -\sum_{i=1}^{m} p_i log_2(p_i) \tag{4}$$

where I represents the expected information that is needed to classify a given sample, S is the number of tuples, and m is the number of coordinates. p_i is S_i/S where s_i is the number of rows of S. After that, the Entropy is calculated. Information gain is the result of I E computation.

3.1.4. Neural Networks

This method uses training data as input. An artificial neural network is constructed and it is used to estimate the position of the MU. The network works like the way biological nervous systems work. The training data is used to teach the system the characteristics of SSs at certain locations and in the positioning phase, the signal sample is given as input to the system and the coordinates of the MU is expected as output[14].

3.2. RF Propagation Loss Models

This approach doesn't need a training phase. Multilateration and the Kalman Filter are representative of localization methods that use the range obtained from the RF propagation loss model to calculate the location of a MU.

3.2.1. Multilateration

In this method, at least three base stations (APs) with known coordinates are required for precise positioning. The distance r from the AP to the MU can be determined in terms of SS and a circle with radius r is drawn. The point where the circles converge is acknowledged as the location of the MU. However, since SS is not a good indicator of distance due to signal strenght distribution is non-Gaussian, obtaining the distance measurement from the SS accurately is almost impossible [15].

$$\begin{bmatrix}(x_1 - x)^2 + (y_1 - y)^2 \\ (x_2 - x)^2 + (y_2 - y)^2 \\ (x_3 - x)^2 + (y_3 - y)^2\end{bmatrix} = \begin{bmatrix} r_1^2 \\ r_2^2 \\ r_3^2 \end{bmatrix} \tag{5}$$

where r_i is the radius of the circle of distance between the MU and AP, x_i is the x coordinate of the AP_i, y_i is the y coordinate of the AP_i, x is the x coordinate of the MU, y is the y coordinate of the MU.

In multilateration method, the positions of APs are so important that they affect the estimated location totally. Under ideal circumstances, the APs should be positioned in the corners and edges of the test environment, so that the coverage of the APs is maximized.

3.2.2. The Kalman Filter

This method repeatedly calculates the location of the MU, and use the previous results to calculate new measurements by linearizing the measurement equation which is a nonlinear model to derive a linear equation [16].

4. Performance Metrics

There are various factors affecting the performance of WLAN-based Indoor Localization Systems. Judging a system by its accuracy on a simple test bed does not provide enough information to evaluate it. Some of the performance metrics are given below [17].

Accuracy: It is widely accepted that accuracy is the most obvious performance metric of Indoor Location Systems. It is, simply, the mean distance error which is the Euclidean distance between the estimated location and the real location.

Precision: Accuracy of a system maybe a wrong indicator to evaluate Indoor Location Systems due to the variety, type and size of test beds. However, precision takes how consistantly the system works into account. Therefore, accuracy and precision should be used together to evaluate a system.

Complexity: When the number of systems, services, and algorithms increases, the system gets less efficient. This also affect the portability of a system due to the changes that should be made to adapt the system into new environments.

Robustness: In wireless networks, it is not always possible to get required data. For example, an interference in the system can prevent you to read RSSI value of an AP which may affect your calculations directly.

Scalability: The area, where the indoor location system is deployed, may be large and have more than one floors. Many researchers doesn't consider this issue while developing their own techniques and systems.

Cost: Indoor Location Systems can be a big added value to a place. However, if this added value gets too costly, people try to find other services to replace it.

5. Experiment

In this experiment, we measured SS data of nearby APs with different MU devices for 24 hours at a certain location. Also, we created a SS map of an AP of our testbed.

5.1. Testbed and Setup

We used METU Computer Center's 2nd floor as our testbed. The map of the floor is given in Figure 4. There are 17 APs visible on this floor, but only one of these APs is in this floor and 2 APs are in the 1st floor.

To collect data, we used 2 different laptops which are (1) Lenovo IdeaPad Y550 and (2) Dell Inspiron 510m. Laptop (1) has Intel Core i5 processor, Windows 7 Professional, 4 GBs of RAM and Intel WiFi Link 1000 BGN wireless network interface and Laptop (2) has Intel Pentium M 1.6GHz processor, Windows XP Professional, 512 MBs of RAM and Dell Wireless 1370 WLAN Mini-PCI wireless network interface.

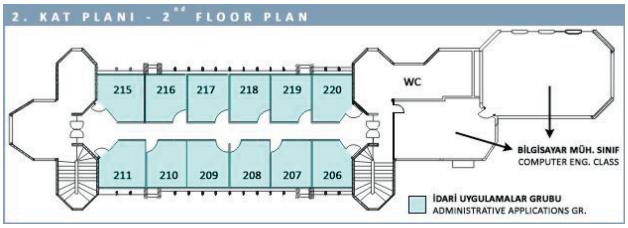

Fig. 4. METU Computer Center 2nd floor plan

5.2. Analysis

Although Microsoft defines that the range of RSSI trigger values is from -10 through -200 dBm, under optimal conditions the strongest value we could get is -20 dBm and the weakest value is -99 dBm.

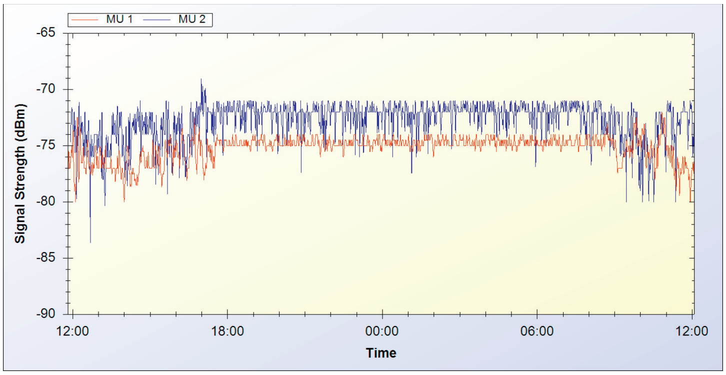

Fig. 5. Signal Strength measurements of an AP with different MU devices

In Figure 5, SS values of an AP are given within a day. The SS values of each AP is read from the wireless device with one minute time interval for 24 hours from 12:00:00 PM to 11:59:59 AM in a room of our testbed building to observe the general change of SS of an AP in time. It can be inferred from this graph that SS can change over time, especially in the working hours of the day when there are a lot of users on the network. However, between 6 pm to 8 am, the SS is fairly stable.

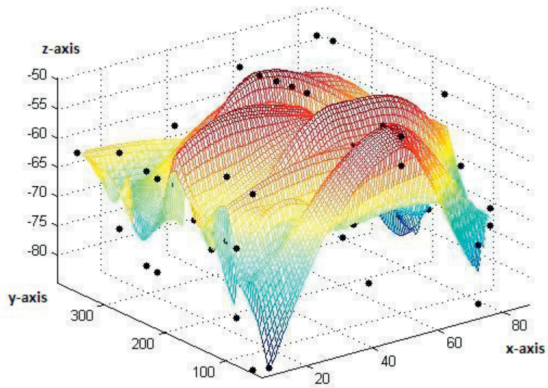

Fig. 6. Signal strength distribution of an access point throughout in our building

As explained before and shown in Figure 6, SS distribution is non-Gaussian over a place, and it can vary with time. The figure shows the SS distribution of an AP in our testbed. In the figure, x and y represent the coordinates of RPs and z shows the received signal strength at that points. The distribution is non-Gaussian. The figure indicates that the SS of an AP at a (x,y) point doesnt depend on the distance between AP and the MU directly. A closer location to the AP can have lower SS than a further point.

6. Conclusion

IEEE 802.11 is the most common wireless protocol beyond debate. It is being used in almost every part of our lives, from home security systems to cell phones, on a wide variety of devices and diverse application domains. This paper surveys the current state of indoor positioning techniques. All of these are still used in active indoor positioning systems despite their tradeoffs. Due to the flexible nature of Wi-Fi, it can be used for various different task in addition to its real purpose. However, different environments, structures, equipments, and people, even climates affect each and every technique differently. Therefore, the place, where such systems will be installed, should be examined and analyzed carefully to establish the right system. To do this, performance criterias should be carefully evaluated. For instance, the balance between accuracy and precision should be well maintained while considering the complexity and robustness. The choice of methodology, data collection strategy, network traffic and user characteristics significantly affects the granularity and accuracy of the localization process.

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