A Survey on Indoor Positioning System using Wi-Fi

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***Abstract*—The functionality of Wireless indoor positioning systems have increased nowadays. Applications used for navigating through a campus or performing inventory management have wireless indoor positioning as its basis. This paper aims to reflect our survey on the development of various techniques and methods used to implement indoor positioning using Wifi. Three Trilateration techniques (TOA, TDOA and RSS) along with Triangulation (basic mathematical technique) are studies and compared on the basis of hardware requirements and accuracy. Later we analyze the technique of location fingerprinting with the help of the above mentioned techniques in an attempt to combine classical positioning methods to minimize hardware usage and increase precision for location detection.**

Index Terms - Time of Arrival, Time Difference of Arrival, Received Signal Strength, Fingerprinting, Scene Analysis, Probabilistic Models, k Nearest Neighbor, neural Network, SVM, SMP.

I. INTRODUCTION

The need for navigation systems has grown significantly, thus a method to localize any indoor location becomes significant to us, Such a system would be essential in places like school campuses ,museums (for guided tours) ,shopping malls (including hypermarkets) and other public buildings maps, where the system would prove as a backbone for location monitoring.

We in this paper study couple of infrastructure-free methods of estimating the location of any object at any position through various techniques using multiple Wifi access points.

The need for this technology is due to the reason that present day localization techniques like GPS, cellular networks, etc. are unable to deliver to localization applications.

This paper also throws light on the development in the local technology over the period of time

We, in our paper, take the distance of an object from different Wi-Fi Access Points (also known as WAPs) as a medium of localization. This method only uses software only and doesn't require any hardware. It works with the current widespread technology and can be implemented with the help of smartphones without any additional sensors.

For instance, the physical and mathematical methods like trilateration, triangulation and fingerprinting can be applied to estimate the location of a user up to 1m-2m. For this signal readings of the user from minimum three different routers will be needed. Also applying machine learning from the collected data would reduce the error to a great extent. The model developed can therefore be used to direct any device inside a campus connected to the Wi-Fi Positioning System to a location that is desired by the user.

This system proves to be highly functional in real life scenarios. For instance, in case of a hospital it can be used to monitor and prevent unauthorized access to patients.

II. TECHNIQUES

A) Trilateration

Trilateration is a geometric method which deals with calculation of physical distances to find position of an object. It can be implemented using the following techniques.

Time of Arrival (TOA)

Time of arrival of a radio signal is defined as the time it takes to travel from a single transmitter to a remote single receiver. All the transmitters and the receiver must be precisely synchronized to get required accuracy as the delay is directly proportional to distance. TOA time obtained is multiplied with the speed of propagation, denoted as c, which gives the distance between the source and receiver. This distance obtained defines a 2D circle with the transmitter as its center and receiver anywhere on the circumference. Intersection of three or more such circles gives the location of the receiver relative to the transmitter. A minimum of three sensors are required to detect an intersection point[1].Timestamp must be labeled in the transmitting signal in order to identify the source of the signal and calculate its distance. TOA can be measured using different signaling techniques such as direct sequence spread-spectrum (DSSS) [2][3][4] or ultra wideband (UWB) measurements [22].There are two main problems in using these (TOA) methods. One is that the synchronization of all the receivers and the transmitter is difficult as the radio waves travel very fast and a small mismatch could result in a great error. Other is that propagation of radio wave depends on the medium in between, if an object comes in between the propagation, it would result in a delay of signal which would be interpreted by the signal as that the transmitter is farther than it actually is.

Time Difference of Arrival (TDOA)

The idea of TDOA is to calculate the position of the mobile transmitter by obtaining the difference in time at which the signal from different transmitters arrives at the receiver, rather than the absolute arrival time of TOA. TDOA obtained is multiplied by the speed of propagation of wave in that medium and TDOA distance is calculated. Thus we obtain a hyperbolic curve on which the receiver much lie .This hyperbolic curve has the two transmitters as its foci. Intersection of three hyperbolas would give the location of the receiver.

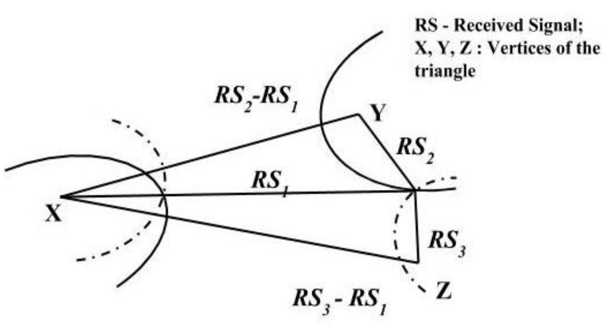

Fig.1. Positioning based on TDOA measurements.

This is better than TOA as it doesn't require the synchronization of the receivers with source. Conventional methods of calculating TDOA is using cross correlation between the received signals. Except this method, a delay measurement-based TDOA measuring method was proposed [5] for 802.

Sources of error in TDOA are similar to TOA which are problem in synchronization of transmitters and noise introduced due to objects in between.

Received Signal Strength(RSS)

Received Signal Strength(RSS) can be defined as the power received at the receiving end of communication system. In this case the mobile application's value of a signal can be used to estimate the distance between the transmitter and receiver. Estimating the signal attenuation due to free space attenuation we can calculate distance using theoretical formulas. One of free space attenuation formulas is given below:

$$Loss = 20 \times \log_{10} di + 20 \times \log_{10} fr + 32.44 \quad (1)$$

where di is the distance measured in km and fr is the frequency measured in MHz. Further, Attenuation can be calculated from the equation given below:

Attenuation = Transmission power - Transmission Cable Loss + Transmitter Antenna Gain + Receiver Antenna Gain - Receiver Cable Loss - Receiver Sensitivity - Fade Margin (2)

Here, the distance can be calculated by the equation given below:

$$\boldsymbol{Distance} = \mathbf{10}(\boldsymbol{Attenuation} - \mathbf{32.44} - \mathbf{20} \times \log_{10} fr) \div \mathbf{20} \quad (\mathbf{3})$$

where the distance is measured in km and fr is frequency of the signal which is measured in MHz.

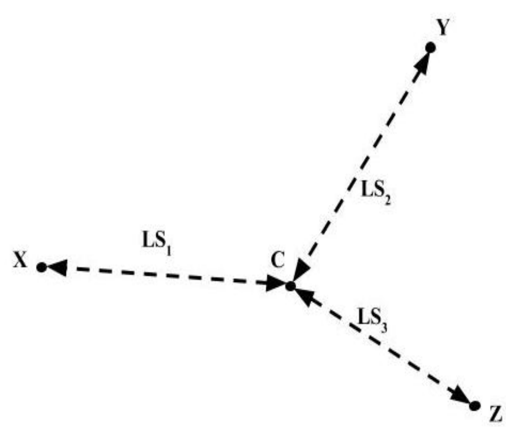

Fig.2. Positioning based on RSS and distance measurements.

This technique does not require any external hardware as value of received strength is available on almost every receiver. It gives successful results for LOS communications in which the characteristics like permeability of the medium of propagation remain constant. But for other cases it fails.

There are many obstructions in real world which cause the permeability of medium to change instantly resulting in greater loss of strength which would be interpreted by the system as the transmitter being far.

Also multipath effect this model can give inconsistent values in some cases.

Due to the above mentioned factors RSS based model are not an accurate technology for indoor positioning systems as they are quite prominent there. This technology can be accompanied with machine learning to in a way find a pattern in the change of medium characteristics and change the theoretical formula accordingly to give accurate results. This is further discussed later in the paper under FINGERPRINTING.

B) Triangulation

The angulation techniques work on the principles of estimation of AOA (Angle of Arrival). Once the angle is determined, position can be estimated by taking the intersection of several combinations of angle direction lines. The real challenge in this technique lies in accurately determining the AOA, as different methods of estimation require hardware setups that might prove to be a limitation in some cases. Methods of estimation of AOA through Antenna Arrays are commonly used in the field of Beam forming and Radar technology. The same methods act as a basis to position objects through Wi-Fi signals.

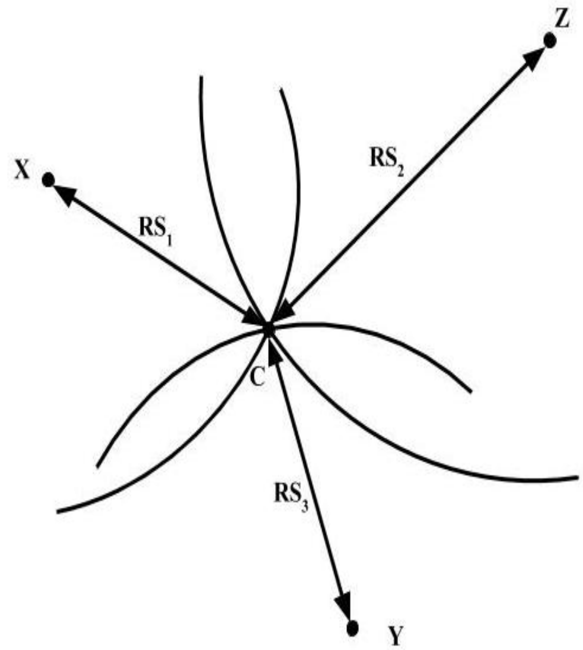

Fig.3. Positioning based on TOA /RTOF measurements.

Some of the most studied techniques in this developing field are the Maximum Likelihood (ML) techniques:-

These techniques were some of the earliest techniques studied for AOA estimation. But due to their intensively computational nature, they could not be implemented more commonly. However, in terms of performance, the ML techniques prove to be superior than most of the other alternatives. These methods prove to be efficient even in low signal to noise ratio and other similar adversities. (For detailed mechanism of this technique, refer to [15])

The shortcomings faced in this method are mostly due the excessive need of precision in angle estimation with increasing distance, in order to maintain the accuracy of prediction of the receiver’s position. But if this is contrived, the method is very easy and efficient in determining position both in 2D and 3D arrangements, with only two and three measuring units required respectively. In contrast to the lateration technique, this method requires no time synchronization between measuring units. Moreover, though the usual setbacks of wireless positioning that are caused by shadowing, multipath reflections etc. are still not completely overcome, this technique still offers a more precise prediction when combined with fingerprinting .

C) Fingerprinting

Fingerprinting is an application of algorithms that use scene analysis. For example, the scene analysis that is based on Radio Frequencies uses algorithms which initially execute fingerprinting of a venue, and then use it to correlate new values with the ones recorded earlier, to estimate the position of an object through matching and online-computations. It is an unusual technique, that uses the signal power to fingerprint, or any other characteristics of the signal that may be used to mark a location on a scene. The incoming signal strengths from different WAPs(Wireless Access Points) are measured and recorded with a location dependent characteristic(dependent preferably almost exclusively on distance from the WAP) for points throughout the location. This print is later matched with obtained values to estimate the location of the device in the scene. Location fingerprinting processes can be divided into two major stages: online stage and offline stage, explained as follows:

Off-line stage: This stage is also known as Training stage or profiling stage. Here, an on-site survey of the site is undertaken. Signal strengths from the WAPs are recorded and locations are labeled with these average values according to various factors such as RSS(Received Signal Strength), AOA(Angle of Attack, TDOA(Time Difference of Arrival), TOA(Time of Arrival). Thus a map is constructed for later reference and matching for prediction of location in the scene using signal strength. This database can be created in 2 or more ways. The first method tries the on-site computations for some base locations in scene using a user terminal. The second method also takes only a limited number of such on-site measurements. It then introduces these values in a propagation model that would make use of these values to fit parameters. An elaborate map with an extensive coverage can be obtained by this propagation model for each WAP. But, unsatisfying outcomes acquired through this model in earlier instances did not agree with our expectations. Yet another method inspired by machine learning for improving such propagation models is the method with Artificial Neural Networks(ANNs). This method effectively improves the model with time(Similar to most machine learning techniques). Ray tracing tools give another approach to building such a database or a map for a scene but are not used here due to their intricate nature.

For the preparation of this database, we have to be aware of the various barriers and adversities (physical as well as of subtle nature) and of methods to deal and cope with such. Awareness of the location of Access points proves to be important. This data is not always accessible due to rapidly increasing emergence of this technique, indoors.

Online stage: This stage is also known as reversing stage. The signal strengths and coordinates previously mapped together are now accessed using a location positioning technique. This technique extracts the recorded metrics to obtain approximate coordinates for a given average signal strength value and some other distinguishing factors(Based on the parameters in the propagation model). The main problems that have to be dealt with arise while recording the new values in accordance with the circumstances that they match accurately with those recorded earlier. Several barriers and hindrances prove to be as obstacles in an accurate estimation of the signal strengths and value metrics(of RSS, TOA, TDOA, etc.).

1.) Probabilistic Methods: A Probabilistic technique has been presented over here[12][13].This technique thinks of positions as classes of a classification problem. The usage of this model provides us with a way to overcome uncertainties in signal power computing. Each calculated signal vector ***Z*** has been assigned a probability which is given by the probability distribution Pr(***Z***|***X***) after calibration for a given position***X*** [26].

We get the following posterior distribution of the scene by applying the Bayes Rule[23]:

$$\Pr[X|Z] = \frac{\Pr[Z|X]\ .\Pr[X]}{\Pr[Z]}$$

$$\Pr[\mathrm{X}|\mathrm{Z}] = \frac{\Pr[\ \mathrm{Z}\mid\mathrm{X}]\ .\Pr[\mathrm{X}]}{\sum_{X_i}\Pr[Z|X_i]\ .\ \Pr[X_i]} \tag{4}$$

where Pr(**X**) denotes the prior probability distribution of existing at the position prior to acknowledging the value of the metric (observation) variable, and the summation is taken over the whole set of potential position coordinates, which can be expressed in a variable **L** [23].

The Prior Probability distribution Pr(**X**) depicts a method which consists of back-end information, like user profile and history of measured signal properties to execute the tracking of the position of an individual. In case both are unavailable, one can use the prior (uniform) information which bring no bias towards a specific position. As denominator Pr(Z) is dependent on position variable a[26], which is considered as a constant, that normalizes whenever relative probabilitiesor ratios are needed. For more information, Please refer here [14].

Suppose that there are k positioning possibilities L_1, L_2, L_3... L_k, and **m** is a vector for the actual signal strength during the duration of on-line stage, the following rule for deciding positions can be obtained:

Choose $\mathbf{L_i}$ if $\Pr(\mathbf{L_i}|\mathbf{s}) > \Pr(\mathbf{L_j}|\mathbf{s})$,
for i, j = 1, 2, 3, . . . , k, j ≠ i.

Here, Pr($\mathbf{L_i}$|**s**) is defined as possibility of the moving node being in position $\mathbf{L_i}$, prescribed that the vector for the reception of signal (RSS) is **a**. Assuming, Pr($\mathbf{L_i}$) as the probability of mobile node being in location $\mathbf{L_i}$, the posteriori probability decides this given rule. By application of Bayes' formula, and due to the assumption that Pr($\mathbf{L_i}$) = Pr($\mathbf{L_j}$) for i, j = 1, 2, 3,...,k, the following decision rule for position coordinates on the basis of likelihood is obtained where P(**m**|$\mathbf{L_i}$) is the probability of signal vector **m** has been achieved, provided moving node is at location $\mathbf{L_i}$

Choose L_i if $P(\mathbf{m}|\mathbf{L_i}) > P(\mathbf{m}|\mathbf{L_j})$,

For $i, j = 1, 2, 3 \ldots k, \quad j \neq i.$

Kernel approach can also compute the probability apart from the usually used Histogram Method. Each positioning candidate can have its statistics computed by assuming the probability of every candidate has been in accordance with the Gaussian distribution. Further, the overall likelihood of one position candidate can be computed by multiplying likelihoods of all measuring units, provided that the measuring units in environment are independent. So, observed Signal strength is used to compute the likelihood of all candidate during the on-line stage, and previous decision rule helps in estimating the position[14][15]. But, it's applicable only for the candidates who have discrete positions. These devices can be located at any coordinates not just at discrete coordinates. The approximated 2D locations $(\hat{x},\hat{y})$ that is given by (4) may give us precise results by interpolating the coordinates of position. It basically denotes the weighted average of coordinates of all sampling locations as given by the formula below [15]:

$$(\hat{x},\hat{y}) = \sum_{i=1}^{n}((P(L_i|m)(x_{L_i}, y_{L_i})) \qquad (5)$$

All other Probabilistic modeling techniques studied may involve pragmatically significant matters such as active learning, calibration, error approximation, and historical tracking for uses such as location-awareness and location-sensitive in field of wireless networks. So, this[14] deals with Bayesian-network based and/or tracking-assisted positioning.

2) k Nearest Neighbor: This algorithm uses the on-line information metrics (of RSS, AOA, TOA, TDOA) to find k nearest sample points in RF-map[25] from the off-line stage database in accordance with RMS (root mean square) error principle. Taking the average of these k coordinate sample points, excluding/including the adopted distances in RF-map space as costs, an estimated position is acquired by kNN which consists of wight as a parameter (WKNN) [16] or contrary kNN which is unweighted (UWKNN). Here, **k** is the parameter that has been adapted for better computations when using this technique [24].

It traverses the database and selects the k sample points which match the records for RSS. The criterion which is usually used is Euclidean distance (in RF-map space) metric. If Z = $[RSS_1, \ldots, RSS_M]$ represents Actual Received Signal Strength vector which comprises of M received APs at unknown location X = (x, y) and Z_i represents fingerprint stored for the position $X_i = (x_i, y_i)$, then the Euclidean distance can be given by [23]:

$$d(Z, Z_i) = \frac{1}{M} \quad . \quad \sqrt{\sum_{j=1}^{M}(\mathrm{RSS}_j\,(x,y) - \mathrm{RSS}_j(x_i,y_i))2}$$
(6)

Where RSS_j (x_i, y_i) are the statistical mean coordinate values stored in the database for the AP whose MAC address is written as "j" at the position (x_i, y_i). The iterative process is used to build the set $N_k$which represents a set of database records having least error [23]:

$$N_k = \left\{\mathrm{argmin}_{X_i \epsilon \alpha}[d(Z, Z_i] \backslash X_i \notin N_{k-1}\right\} (7)$$

Where L represents the set of all positions recorded in database, which contains **k** no. of values corresponding to **k** position. Lastly, the position of the mobile under observation is taken as the barycenter of the k selected positions (mentioned above) it is given by[23]:

$$X = \frac{\sum_{j=1}^{k}(1/d(Z, Z_i))\ .\ X_j}{\sum_{j=1}^{k}(1/d(Z, Z_i)}\text{with } X_j \in N_k \qquad (8)$$

This technique's simplicity is one of its main advantages over the other methods for fingerprinting. Although, the precision is highly dependent on the granularity of the test (or reference) database [16][17], much more precision can be attained by more complex and fine grids, but such a grid requires a much larger database that is highly inefficient in terms of Time complexity.

The disadvantage of using the kNN method is its reduction in the precision when the size of the database is increased considerably. Hence, accuracy is inversely dependent on the database size.

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3) Neural Networks: In this technique the neural networks are trained on the basis of RSS and corresponding location which serve as input and target respectively. Mostly, Multilayer Perceptron Network is used in positioning systems that are based on neural networks' technique. Multilayer Perceptron Networks (MLPs) use a hidden layer for computation purposes. The data is trained and the weights are obtained. This weight matrix is multiplied by the input vector signal strengths which is further added to the input layer bias, if the bias is chosen. The result thus obtained is fed to the transfer function of the hidden layer neuron. The result of the transfer function is multiplied to the weight matrix of the hidden layer and added to the bias of the hidden layer (if chosen). The output obtained is a vector having 2 or 3 elements which is the required position of the object in 2D or 3D space respectively.

4) Support Vector Machine: Used in the classification of data and regression, this technique performs significantly well in statistical analysis and ML (machine learning). This technique finds its application in fields like physical

science, theoretical science, engineering, medicine, etc.[18] [19].Support vector regression (SVR) and support vector classification (SVC) of numerous classes had been mentioned in location fingerprinting [20][21]. Also, the theory of SVM is found here [19][5].

5) Smallest M-vertex Polygon: This technique is used to form an M-vertex polygon by using on-line received signal strength. It searches sample points in space by using the received signal strength from transmitters and thus makes M-vertex polygons from say M-transmitters. By taking the average of the vertices of the smallest polygon (having smallest perimeter) we get the estimated position of the object. It has been used in MultiLoc [21].

III. CONCLUSION

The paper thus surveys and affirms that the aforementioned technology is the most appropriate for aspects of indoor localization like navigation and object tracking .The techniques studied in this paper are simple and easy to implement .Machine learning imparts the system further robustness and flexibility and helps the system to adapt to changes over time and according to environment. Thus the system best finds its application in various corporate and domestic environments.

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