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Abstract—**Indoor Localization using Wi-Fi is gaining ubiquitous usage owing to its simplicity and inexpensiveness. A conventional method of localization is trilateration which can be accomplished using signal strength or time of flight of a radio signal between reciever and transmitter. However trilateration is prone to errors in accuracy which can occur due to various factors. Commonly, a reason for the failure of trilateration is due to the errors in distance estimation which makes the quality of trilateration poor. In this paper, we propose a novel Weighted Adaptive Location Estimation (WALE) algorithm. The proposed algorithm improves the accuracy of localization over the basic trilateration by taking into account the quality and properties of the circle overlaps in the trilateration region. Based on the overlap properties a distance reestimation, and classification of points based on whether they are trilaterable is performed. A maximum likelihood estimation over a weighted grid of this region based on an exponential distribution provides the location estimate. Our experiments over real indoor testbeds have demonstrated that our algorithm provides much improved accuracies without fingerprinting both in the average and worst case.**

I. INTRODUCTION

Localization and tracking has become ubiquitous in these days of smart spaces and smart environments. It plays a major role in improving shopping experiences by observing buyer patterns in malls, providing fast and effective disaster response and making spaces ambient and energy efficient based on user behaviour. In most of these localization applications, WiFi is the preferred mode since it is ubiquitously present.

WiFi localization works by locating a WiFi receiver using parameters like RSSI, Angle of Arrival(AoA), Time Difference of Arrival(TDoA), etc. Parameters other than RSSI require specialised hardware or require us to look at lower layer IEEE 802.11 protocol and proper synchronization. That is, the signals may not be received in the order that they are sent. Whereas, RSSI can be easily obtained from standard mobile devices. Therefore RSSI, is more commonly used for localization, despite its inaccuracies [1]. Localization techniques that use RSSI primarily rely on fingerprint maps which are labour intensive to generate. However, these techniques provide reasonable accuracies of 4-6m [2]. While there are a few non-fingerprinting approaches that use RSSI as the base parameter, they suffer from poor accuracies. The labour involved in fingerprinting techniques and the low reliability offered by non-fingerprinting techniques open up avenues for further research in developing better and robust non-fingerprinting localization algorithms.

In this context, trilateration is one of the most well known methods for localisation. Trilateration is the process of finding the center of the area of intersection of three spheres. We are using circles to represent distance from a router and as such we will only be needing a point and not the area. The center point and radius of each of the three circles must be known, this is location of routers and distance obtained from RSSIs respectively. There are higher level methods such as multilateration, but using the best 3 routers' RSSI value to obtain a localised point is the best approach in our case.

The Least Square Method is also one that we considered. How we do this is, For N beacons, we obtain N equations (equation of a circle) and subtracting the N-1th equation from the rest, we obtain a linear system, which can be approximated using Least Squares. This again involves us taking a minimum of 4 routers and hence this method is not optimally suited in our scenario but is worth considering once we expand.

In Trilateration, it is observed that more often than not, the circles don't intersect. This is caused due to more signal strength loss than initially predicted. We empirically find a path loss exponent 'n' , which we use throughout our experiment. This value however, isn't perfect and causes inconsistencies from what is actually expected. This miss correlation of data occurs from differences in environment within our experiment region which are unavoidable in real scenarios of localisation. Thus, we may classify our data set to 2 cases where Trilateration is possible and where it is not.

We divide each of our circles into 3 bands of based on their radii circle. Also when distance is represented as a measure of probability, we find that the probability of the point lying in a fuzzy band near the border of the circle is higher than the center[insert reference here]. By considering the log-distance propagation model, we come up with an approach that does a 'weighted adaptation'

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succeeding trilateration, where weights are a function of the radius and follows a logarithmic curve. This approach is modified according to which case the node(i.e device) corresponds to. For future reference, we will be using device/node interchangeably to represent the point that is being estimated and beacons/routers to represent the 3 routers.

II. Related Work

Most of the RSSI based systems, operate upon on either of the two major variables: Time or Distance. Time based localization [3] techniques rely upon either specific hardware [4], information extracted from channel state information or make essential assumptions about the area. Techniques reliant upon distance use propagation models to better map the RSSI to a distance and then perform multi-laterations to accurately localize the area. Trilateration while easier to implement has very low accuracy owing to the lack of perfect distance propagation models. Hence fingerprinting is often clubbed together with the multilateration techniques. But its dependency on radio-maps, which have proved to be laborious and time-consuming, is also fickle due to its reliance on the environment. Algorithms such as [5] proposed, aim to improve accuracy but they fail due to the poor stability of the 2.4 GHz band.

WiFi localization techniques fall into numerous categories. Several location estimation techniques attempt to model signal propagation through space [6], assuming known locations of access points and an exponential signal attenuation model. However, even when taking into account furniture and walls of different material the accuracy is limited. There are other techniques that attempt to localise using RSSI fingerprint data using a Markov model, kNN based approach, for example [7] focused on baby tracking in an indoor environment which proved to be effective, however, it will become onerous when shifting to an unknown location. While more accurate than signal propagation models, these methods are inherently discrete and have only limited capabilities for interpolation between locations.

Wireless Sensor network need to establish links between them for initial connections. Previously this was done using snooping or flooding techniques. Now an RSSI based approach [8] is being used because establishing these links in an unsymmetrical environment yields unsolicited results. Also in a WSN approach [9], uses database switching as per the position of reference node need to be done. This helps in switching from indoor to outdoor environments, but requires complete knowledge of the area, otherwise error percentage will increase. Other experiments [10] showed that although the accuracy of RSSI received at a single antennae is highly fluctuating, a Feature Vector which is formed by lots of RSSI values from different APs is a certain stability. This algorithm was able to obtain accuracies ranging between 2m-4m. However, to obtain this Feature Vector the localisation region is divided into grids which requires extensive work to implement. Moreover, after obtaining the Feature Vectors in real-time, they are compared to existing Fingerprinted Feature Vectors to obtain this accuracy.

Systems such as [6], uses signal strength and signal to noise ratio along with triangulation, Ekahau [11], in addition to signal strength requires extensive site surveying to calibrate the underlying localization system, while accurate are expensive to implement and time-consuming. [11] also uses signal strength but in addition it requires a site survey to calibrate the system and WiFi location tags to be present on the user. These IPSs are susceptible to several factors that affect the RSSI and hence subsequently reduce their accuracies. COMPASS [12] takes the orientation of the user into account but it also is reliant on an elaborate fingerprint of the target area which is laborious. There are also a multitude of systems that are hybrid variants and use various other technologies such as Bluetooth, RFID, Infrared in addition to WiFi. Perez et al. [13] propose a system where trilateration is performed using the signal strength of the Bluetooth waves and then an approximate localized region is obtained. Techniques such as these inculcate specialized hardware which makes them expensive to deploy and test. Hence our aim is to minimize the cost and develop a system that works with the existing infrastructure. In this paper, we devise an approach that aims to solve the aforementioned issues by suggesting a cost effective method that doesn't compromise on the precision of localization.

III. Analysis of Trilateration

As discussed in previous sections it is important to develop non-fingerprinting based solutions for indoor localization. Additionally, such solutions should preferably work with signal-strength information since they do not require additional hardware. Trilateration is a basic non-fingerprinting approach, which is robust and easy to implement but suffers from poor accuracy. However there is scope to adapt and improve trilateration. Towards this we have analyzed the performance and patterns in trilateration and identified the potential areas for improvement and this section goes into the details of this analysis.

Firstly we discuss the target environment where we conducted our experiments to analyze the performance of trilateration. The target environment is a typical office space with several cubicles and pathways for walking which is analogous to normal indoor settings. Belkin N600 DB Wireless Dual Band N+ Routers were used to collect the dataset. To achieve the optimal coverage of the area, four routers are strategically placed such that the variance amongst them is maximum [14], [15]. Additionally, the router's relative position from the ground also plays a pivotal role. The RSSI variance between routers influences the optimal positioning, and after analysis [16] , it was observed that for any point , for precise localization, three routers at a maximum distance of 18 m away from each other were required. To eliminate any shadowing due to obstacles, the routers were placed up high (2.43m) [16], which also aids in maintaining a line of sight with minimum path loss at each point. Thus the routers were positioned as shown in 1.

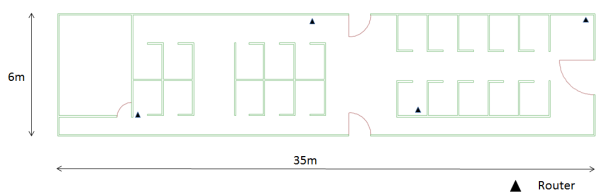

Fig. 1. Localization area

Several experiments were conducted in this environment, primarily for fingerprint data collection over several iterations and for localization experiments [16]. Additionally experiments were performed to understand the path-loss in different environments. Our analysis of the trilateration has been conducted over several of these experiment data sets. We first performed trilateration over several points in the fingerprint databases and calculated the overall accuracy [16]. On probing the results, we find that for the majority of the points the intersection region was inaccurate. Hence we used non linear least square regression to better find the probable region, which is a method to approximate the modelling region to a linear one and refine it in succeeding iterations. In this environment, We noted an average accuracy of 7.76m with a maximum of 21.49m and in the best case scenario it was .64m .

The accuracy definitely needs to be improved, therefore warranting further analysis. Upon further examination, it was discerned that the source of this discrepency could be attributed to the error in distance estimation. Distance estimation is based on appropriate distance propagation models.

There are several propagation models that exist. Models such as Hata-Okamura, Log distance path loss, ITU etc. are dependent on the log-distance equation to model the signal pathloss. These models are widely accepted due to being derivations of the Free space path loss model, which originates from the inverse square law and the antenna gain. For our experiments, We consider the log distance path loss model as our RF propagation model [17], [18].

$$\left[\frac{P_L(d)}{P_L(d_0)}\right]_{dB} = -10nlog\left(\frac{d}{d_0}\right) + X_{dB} \qquad (1)$$

Where:

- PL(d0) is the total path loss measured in (dB) at a distance d0.
- PL(d) is the total path loss measured in (dB) at the distance d1.
- 'n' is the path loss exponent. which has been empirically found out to be 3 in our case.
- 'X' is a zero mean Gaussian distributed random variable (in dB) with standard deviation σ. Since the shadowing effect in our experiments is inconspicuous and can be ignored, 'X' is equated to 0

While the log distance path loss model takes shadowing into account, it still is founded upon empirically derived evidence and does not hold good in all environments. The path loss exponent is an important parameter and not choosing an appropriate value could considerably alter the end results [19]. Thus the dependence of the path loss exponent on empirical results coupled with its mercurial nature to be easily influenced by environmental factors evidences the fickleness of propagation models. Our goal here is to identify the ramifications of these factors on trilateration and methods to alleviate the error, and not the factors themselves. For this, we look at the geometric patterns of the circles and their impact on the accuracy. Taking that into consideration, we look into the overlapping region of the circles. It was observed that two major reasons contributing to the failure of trilateration due to an unfavourable overlapping regions were underestimation and overestimation.

Underestimation occurs when the circles do not intersect each other in a manner to distinctly find a common region among them. It can be observed in either of these probable possibilities viz. three completely non intersecting circles, one circle intersecting with two others and only two circles intersecting. Hence localization becomes inherently improbable as there is no common region between the three circles to leverage out a point to accurately depict the actual position of the device. After the evaluation of trilateration in our dataset, underestimation in one form or the other occurred in around 57% (48 instances) of the cases.

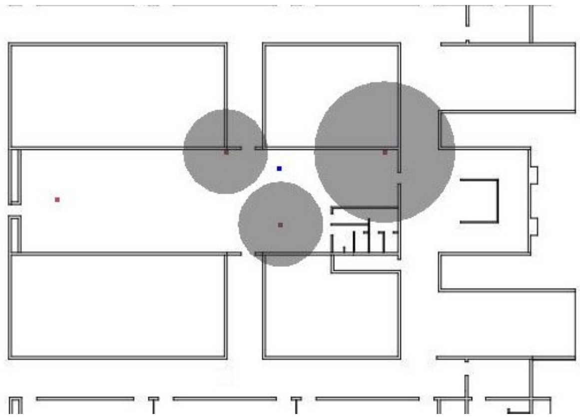

Fig. 2. Practical Example of Underestimation

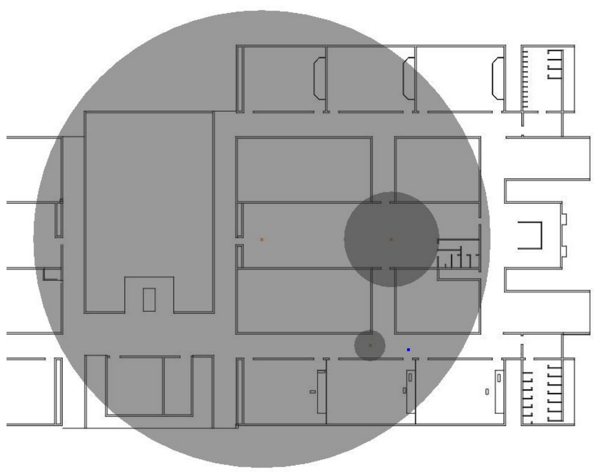

Fig. 3. Practical Overestimation Example

Conversely, Overestimation occurs when one circle completely encompasses the other circle(s). In such cases, the intersecting region is a large ambiguous area where localization becomes improbable. Typically, when the intersecting region is large its centroid is considered to be estimated point. But in such cases, this becomes meaningless as the centroid lies near the centre of the larger circle. Overestimation accounted for xx% of the cases in the second environment.

It was also observed that for a substantial number of cases, when the radius of the second smallest circle exceeded that of the smallest by a factor of β the position of the device was in close proximity to one of the routers and lied near the outer regions of the smallest circle.

Thus to alleviate this, A recalibration of the estimated distance would result in better localization. This recalibration could be achieved by either systematically increasing the radii of the three circles till they intersect or by decreasing them till the intersection region is meaningful [5]. In cases of close proximity, It could be discerned that the likelihood of the device existing

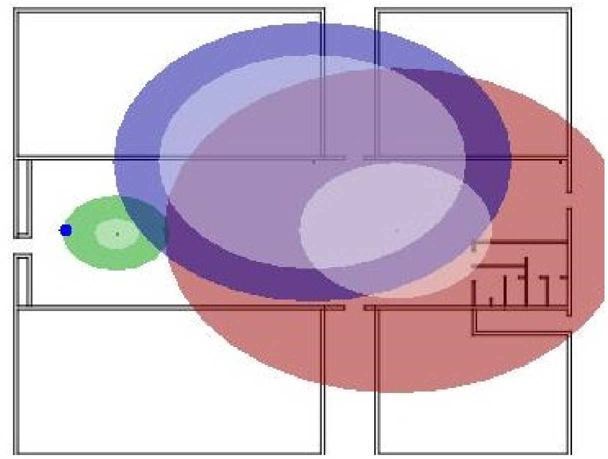

Fig. 4. Practical Overestimation Example

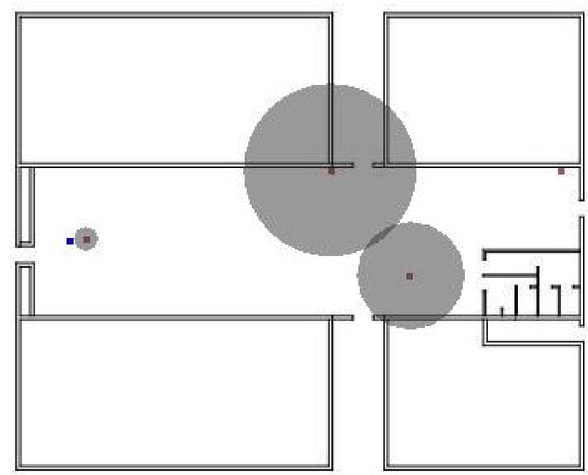

Fig. 5. Device close to a router

near the circumference was higher than it lying near the center. Hence, the overall system could be bifurcated into major sections; One requiring trilateration and the other not. The former could be further classified into three sub sections viz. Normal trilateration, underestimation and overestimation.

In our paper we use these insights to propose WALE (Weighted Adaptive Location Estimation), an algorithm that combines a probabilistic weighting approach with a dynamic circle resizing approach. The approach is customized based on whether a point is trilaterable or not. The next section will explain our algorithm in detail.

IV. Weighted Adaptive Location Estimation

We describe our approach to improve the indoor localization without fingerprinting by designing a Weighted Adaptive Location Estimation Algorithm over the basic trilateration. This approach is based on three major aspects:

- Identifying whether trilateration is feasible for a given location estimation or not
- Determining whether the distance estimation from the routers has been underestimated or overestimated based on the trilateration pattern and accounting for it.
- Using a novel weighting function that assigns weights with higher probability to points nearer the re-estimated boundary of a disc, and lowest probability towards the center.

Based on this the overall outline of our approach is as follows. For a given point, the distances to the three nearest routers are estimated using the log-distance model. Based on the ratio of the distances the points are classified as whether they can be trilaterated or not. The distances also provide an indication of the type of overlap of the three circles in trilateration and thereby the quality of trilateration. This gives us an idea if the distance is underestimated or overestimated per router. We develop a novel distance re-estimation algorithm which modifies the radii of the circles. A weighting function is applied across the radius of the circle to estimate the probability of a point lying at any potential distance from the center. Using this function, and the classification we come up with an algorithm that calculates the maximum likelihood position. The rest of the section will explain our algorithm.

A. *Classification of Location Points*

Once a device sends its RSSI for different routers we can estimate whether it

a candidate for trilateration or not. When we say a point is a candidate for trilateration, we mean that it's position is usually within an overlapping region within the influence of all three routers. If it is not a candidate, we believe that despite distance reestimations, the point is either within one router's influence region or outside all three. In such cases trilateration will give a big error. Consider Now talk of the classification approach....Give figures and exisamples and our algorithms

Analyze three radii... Categorize based on ratio of smallest and next smallest circle radii..how do we fix this ratio? How is "0.55" or the separation value set?

Second part...

Explain how we say under-or over-estimation based on the circle overlaps or lack of it. Then our algorithm followed by brief explanation.. Justification for why cyclic..we need to say two aspects influence - 1)when rssi is strong it is more likely to be right, so resizing should be minimal for that router 2) when two circles are close or nearly intersecting, it should also be considered (DCE does this). So we go for an approach that considers both...since it resizes from the largest, but once overlapped we dont continue increasing..Some justification/examples to say why choosing one of the two alone wont be sufficient.

Finally how to choose by how much to increase..can be conservative..this would increase complexity...otherwise it would be over increasing or decreasing..so experimentally it has to be decided. For our case 10 percent worked...

Apply cyclic resize algo - increase if they don't meet, decrease if circle completely covers other two circles...

Third part..

Our weighted-.. algorithm based on category.

Explain the weighting function...with figure Then the algorithm Maybe complexity

Algorithm

Result: Circles with meaningful intersection region
while $C[0].getFlag() == 0 ORC[1].getFlag() == 0 ORC[2].getFlag() == 0$ **do**
  $i = Q.deQueue()$;
  if *!(C[i].isOverlap(C[(i+1) mod 3]) AND C[i].isOverlap(C[(i+2) mod 3]))* **then**
    increment($R^{'}$, α) $Q.enQueue()$ **end**
    else
      if *C[i].isEnclose(C[(i+1) mod 3]) OR C[i].isEnclose(C[(i+2) mod 3])* **then**
        decrement($R^{'}$, α) $Q.enQueue()$ **end**
      end
      else
        C[i].setFlag(1) ;
        Q.enQueue();
      end
    end

Algorithm 1: Algorithm for Distance Estimation

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Result: Location estimate of device
for $i \leftarrow 0$ *to* 2 **do**
  for *Each* (x, y) *in* $C[i]$ **do**
    $rad = C[i].getr();$
    $dist =$
    $Distance(x, y, C[i].getx(), C[i].gety());$
    $currWeight = (1/rad) * (e\ (dist/rad));$
    if *IsTrilaterable*(θ) **then**
      $W[x][y] = W[x][y] + currWeight;$
    end
    else
      $W[x][y] = W[x][y] - currWeight;$
    end
    $W[x][y] = abs(W[x][y]);$
  end
end

Algorithm 2: Algorithm for calculating Weights

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