Locating WiFi Access Points in Indoor Environments using Non-monotonic Signal Propagation Model

Saeed Varzandian
Advanced Control Systems Lab
Tarbiat Modares University, Tehran, Iran
Email: saeed.varzandian@modares.ac.ir

Hasan Zakeri
Advanced Control Systems Lab
Tarbiat Modares University, Tehran, Iran
Email: hasan.zakeri@ieee.org

Sadjaad Ozgoli
Advanced Control Systems Lab
Tarbiat Modares University, Tehran, Iran
Email: ozgoli@modares.ac.ir

***Abstract*—In this paper it is shown that the widely used log-normal path loss signal propagation model may not be a good choice for every indoor environment. Instead, a non-monotonic signal propagation model for an indoor environment is presented. This model, combined with received signal strength values, relative distance and directional information can exhibit several applications. As an example, access point position estimation is studied in this paper and an algorithm is proposed for this purpose. It is shown that using relative distance, directional information and an arbitrary reference point, it is possible to find the relative location of access points. The performance of proposed model and algorithm is tested by real data and computer simulation.**

***Index Terms*—Indoor Localization, WiFi Positioning, Non-monotonic Signal Propagation Model**

I. Introduction

Localization has many applications in various fields such as robotics, traffic management, routing, aviation, tourism, etc. In fact, in robotics, one of the early steps of controlling a moving robot is to know its position in the space in order to find its way to a desired target. On the other hand, the growth of wireless communication technologies in recent years, specially IEEE 802.11 standard [1] (also known as WiFi) and its low cost and availability almost everywhere, make it a good basis to develop localization systems. WiFi is specially designed to have perfect communication performance in indoor environments. Nowadays WiFi access points are available in almost every public urban area such as universities, hospitals, airports, museums, etc. Contrary to the Global Positioning System (GPS), which losts its use in indoor application, WiFi technology is a good infrastructure for developing indoor localization systems.

Several algorithms have been proposed recently for positioning, but generally, they can categorise as *traditional triangulation, scene analysis* and *proximity methods* [2]. In scene analysis methods some features called fingerprints of the scene is needed for location estimation to generate a fingerprinting map. In the next step, online measurements are compared with the map and the position of the closest fingerprint is selected as the target position [3]. Generating a fingerprinting map is a time consuming process [4]. The idea of proximity method is when a target is detected by an antenna, it is considered to be collocated with that antenna [2]. Because of poor accuracy, this method is not proper for small areas with low number of antennas. The most simple and famous method of localization is triangulation. In this method the geometric properties of triangles is used to estimate the location of a target [2]. Basically, triangulation has two derivations: lateration and angulation. In lateration method the position of an object is estimated by measuring its distances from different reference points. The angulation method computes angles relative to multiple reference points to locate an object [2]. The above methods need a function to describe the received signal strength (RSS) and distance relation. One of the most commonly used models for RSS at indoor environments is the log-normal path loss model [5], [6].

There are location estimation softwares such as RADAR and PlaceLab that are developed under WiFi technology but these softwares does not work properly indoor [7]. A system for multisensor and collaborative localization is presented in [8] that aims to fuse location information from different systems such as GPS, RFID-based, cellular positioning systems [9] and optical systems for localization in diverse environments. In [10] an algorithm for finding access point location is presented which is for outdoor use. The authors do not mentioned anything about the propagation model. In [11] the authors used the Monte Carlo Markov Chain (MCMC) technique to fuse the WiFi RSSI information and the inertial sensors measurement. They used the log-normal path loss model. They implemented their method on a smart phone and tested it in an office environment. In [12] an integration of WiFi positioning system with inertial sensors is presented to smooth the noisy scattered WiFi positioning and reduce sensor drifts and then authors applied a fast feature reduction technique to fingerprinting. This is done in order to identify the WiFi access points with highest discrepancy power to be used for positioning. In [13] authors tried to fuse WiFi measurements with dynamics of human movement and propose a data-driven movement model. This model is used to make a single cellphone-based indoor positioning system. In [14] authors proposed a method which locates WiFi access points in an unsupervised manner using

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radio scans collected by a smart phone. This method finds relative positions of access points based on multidimensional scaling technique [15]. This needs heavy calculations when the number of access points is high.

In this paper it is shown that using the log-normal path loss model may not be an appropriate choice in every indoor environment. Then an alternative signal propagation model is introduced and then an algorithm based on that is proposed. This algorithm needs RSS values and relative distance and directional information. The proposed algorithm is simple, does not need heavy calculations and can be easily implemented on smart phones.

This paper is organized as follows. In section II a simple triangulation method that is used in this paper is described. In section III the log-normal path loss model and the proposed signal propagation model are studied. In section IV the proposed algorithm is described in detail. Sections V and VI present the simulation results and concluding remarks, respectively.

II. Triangulation Method

A simple triangulation method that is used in the proposed algorithm is described here. Consider three points in two-dimensional space: (x_1, y_1), (x_2, y_2), (x_3, y_3) with known positions and also consider there is a target point (x_t, y_t) with unknown position. The distance of each point from the target point is known as d_1, d_2 and d_3. With this information, it is possible to find the target location as the crossing point of circles c_1, c_2 and c_3, as in Fig 1. This is a key idea to the algorithm presented in section IV. But first, a signal preparation model is introduced.

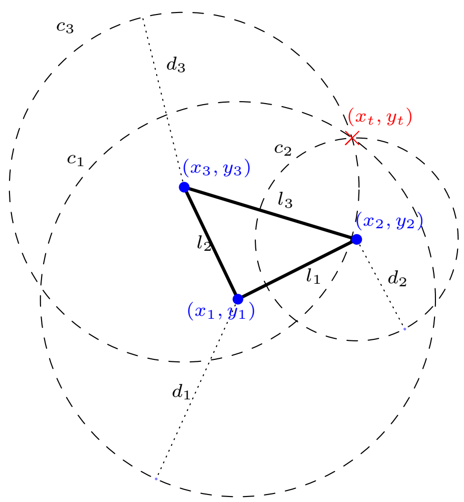

Fig. 1: Finding the target (red) using triangulation methods

III. Signal Propagation Model for Indoor Environments

The signal propagation model in indoor environments is totally different from the outdoor one. Signal propagation in indoor environments is more complex because of several factors, including multipath, shadowing effects and etc [6]. A widely used channel model for RSS-based localization in indoor localization systems is the log-normal shadowing path loss model [5]:

$$L_p = L_0 + 10\alpha \log_{10} d + v \qquad (1)$$

Where L_0 is the signal power loss (in decibels) at $1\mathrm{m}$ distance, L_p is signal power loss at a distance d ($d \geq 1m$), α is path loss exponent, and v is a zero mean Gaussian random variable representing log-normal shadow fading effects in multipath environments. According to this model, the RSS depends logarithmically on the distance. As shown in (1), the distance is a monotonic function of RSS. However in indoor environments the behavior of propagation channel is totally different. Fig 2 shows the results of RSS-distance measurements in an indoor environment (Details will be discussed further). The best fitted log-normal curve for this data is also shown in the figure for $L_0 = 3$ and $\alpha = 2$. It is obvious that fitting a log-normal path loss model is not a wise choice for such a data. Instead, a proper polynomial curve could be employed. However, driving a polynomial model has another issue; the polynomial function representing the relation between RSS value and distance is not monotonic. In other words, the distance as a function of RSS is not single-valued hence by knowing RSS it is not possible to get the distance. Therefore, more information from environment is required. An algorithm is presented in section IV to find the relative location of an access point using the non-monotonic RSS-distance function, RSS values, relative distances, directional information and an arbitrary reference point.

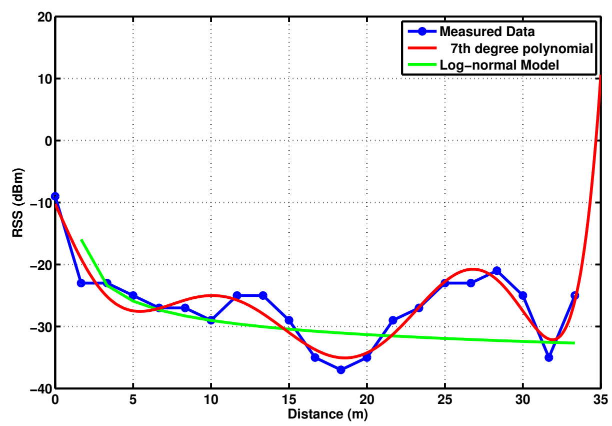

Fig. 2: Measured data for an indoor environment (a corridor), a log-normal model and a 7th degree polynomial as the fitted curve

The proposed model is a 7th degree polynomial fitted to the experimental results. For gathering RSS data, a corridor of about 3.5m width and length of 36m is selected. The access point (the target) is placed at the end of the corridor. The received signal strength is measured 5 times for each 24 selected test points (each point 55cm away from its neighbor). Omni-directional antennas are used in both transmitter and receiver sides in order to have more trustful measurement. The receiver is *TP Link TL-WN7200ND* wireless USB adapter installed on a laptop computer, and the transmitter is a *HUAWEI BM632w* WiFi access point. During the measurement, there is no network traffic on the access point. In addition a low-traffic transmission channel is selected in order to avoid possible conflicts with other access points. Working in the area, the measurement is made in a holiday to avoid the effect of people moving around. Having the measured data, a polynomial curve is fitted to the data and selected as the signal propagation model for the test environment (department corridor). See fig 2 for details.

The RSS data can be approximated as

$$RSS = p_1 d^7 + p_2 d^6 + p_3 d^5 + p_4 d^4 + p_5 d^3 + p_6 d^2 + p_7 d + p_8$$

where the values of p_1 to p_8 are given in Table I. This model can be used for severall indoor applications.

TABLE I: Parameter values

p_i	Value
p_1	4.6392e-07
p_2	-4.9208e-05
p_3	0.0019645
p_4	-0.035942
p_5	0.27922
p_6	-0.32586
p_7	-5.3861
p_8	-10.246

IV. The Positioning Algorithm

Consider three points (x_1, y_1), (x_2, y_2) and (x_3, y_3) in a two-dimensional space with known RSS information as (RSS_1, RSS_2, RSS_3) and relative distance and angle from each other (l_1, l_2 and θ_1, θ_2) as in Fig 3. The distance from each point to the target point (d_1, d_2, d_3) is needed in order to find the target location. Consider a polynomial curve as the signal propagation model. Since the signal propagation model is generally a non-monotonic function, each RSS value might lead to more than one possible distance. This is the problem that occurs in indoor environments, but in the outdoor case, as the signal propagation model is monotonic (usually as a log-normal function,) there is not such a problem.

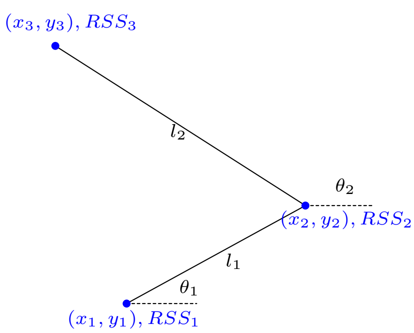

Fig. 3: How to gather data in the proposed algorithm

Generally, three circles can have up to six crossing points in the space, as in Fig 4. In order to find the exact location of the target point, all the three circles must have a common crossing point (fig4-a). As mentioned earlier, in the indoor localization problem it is possible to have more than one distance for each RSS value, hence there are lots of possibilities for having $(d1, d2, d3)$ triplets. Not all of these triplets can lead to a common crossing point (e.g. fig4-b). In fact there are some triplets that make circles which do not have enough crossing points or they have no common ones at all. Therefore the number and arrangement of the crossing points in each case has to be checked in order to find a candidate. This process can be done in two stages. At first, the triplets that their corresponding circles do not cross with each other are removed. In the second stage, for remaining triplets, the distance of each crossing point from the others is measured and the crossing points in triplets that have crossing points near enough to each other (according to a certain threshold) are selected as the target position.

Here is the pseudo code of the proposed algorithm:

1) Choose an arbitrary position as p_1 and set $p_1 = (0, 0)$. Measure RSS_1.
2) Move to an arbitrary direction and distance (p_2). Measure RSS_2, l_1, θ_1. The position of p_2 is then calculated as $(x_2, y_2) = (l_1 \cos(\theta_1), l_1 \sin(\theta_1))$.
3) Move to an arbitrary direction and distance (p_3). Measure RSS_3, l_2, θ_2. The position of p_3 is $(x_3, y_3) = (x_2 + l_2 \cos(\theta_2), y_2 + l_2 \sin(\theta_2))$.
4) Move to an arbitrary direction and distance (p_4). Measure RSS_4, l_3, θ_3. The position of p_4 is$(x_4, y_4) = (x_3 + l_3 \cos(\theta_3), y_3 + l_3 \sin(\theta_3))$.
5) Find the corresponding distance values of RSS_i using the signal propagation model $(d_{i,j})$ where j is the number of possible distances, i.e. find the roots of:

   $$p_1 d^7 + p_2 d^6 + p_3 d^5 + p_4 d^4 + p_5 d^3 + p_6 d^2 + p_7 d + (p_8 - RSS_i)$$

   (notice that there might be complex values which are not desired. As the desired parameter is distance, only real and positive values must be considered.)
6) The candidate triplets for (d_1, d_2, d_3) are $(d_{1,j}, d_{2,j'}, d_{3,j''})$. Eliminate triplets that do not meet the constraint: $|d_{i,j} d_{i+1,j}| \leq l_{i-1}$ $(i = 1, 2)$
7) Eliminate triplets that do not meet the constraints:

   $$|d_{1,j} d_{2,j'}| \leq l1 \leq d_{1,j} + d_{2,j'}$$
   $$|d_{1,j} d_{3,j''}| \leq l2 \leq d_{1,j} + d_{3,j''}$$
   $$|d_{2,j'} d_{3,j''}| \leq l3 \leq d_{2,j'} + d_{3,j''}$$

   Note that these constraints come from triangule inequality.

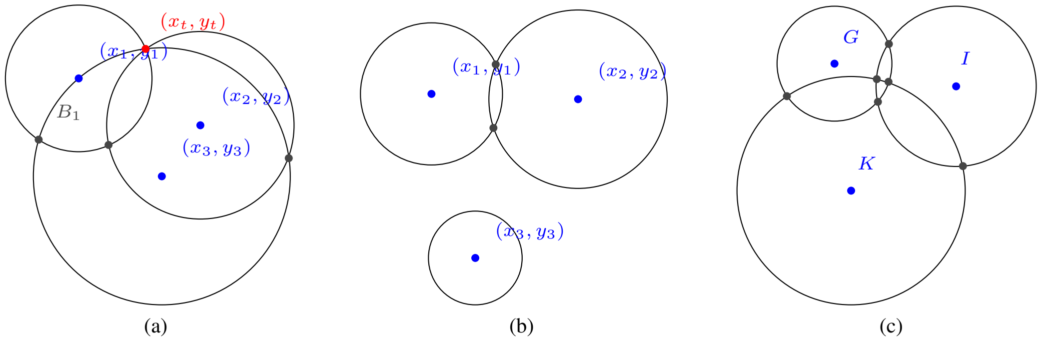

Fig. 4: Different cases for the proposed algorithm

8) Find the crossing points of circles of each triplet:

$$(x-x_1)^2+(y-y_1)^2-d_{1,j_2} = (x-x_2)^2+(y-y_2)^2 d_{2,j_2''}$$

$$(x-x_1)^2+(y-y_1)^2-d_{1,j_2} = (x-x_3)^2+(y-y_3)^2 d_{3,j_2''}$$

$$(x-x_2)^2+(y-y_2)^2-d_{2,j_2'} = (x-x_3)^2+(yy_3)^2 d_{3,j_2''}$$

All of the above equations must satisfy simultaneously. In this step the equations have one or two solutions (crossing points). Cases with no crossing points were eliminated in step 6. Assume that for each triplet, the number of all solutions of above equations is n.

9) Let

$$C_k = \begin{bmatrix} x_{1,k} & y_{1,k} \\ & \vdots & \\ x_{n,k} & y_{n,k} \end{bmatrix}$$

be the vector of solutions for k^{th} triplet. If there are three same rows in C_k, it means that the three circles have a common crossing point which is the position of access point. Find the triplets that have common rows. In real cases in which there are propagation model errors, sometimes there are no crossing points. Instead the points are near to each other. Therefore a threshold has to be defined to find the neighboring points. If a unique position for access point is found, the algorithm ends. If not go to step 10.

10) In cases that there is no solution for access point position or there are many access point position candidates, data from the fourth point (p_4) has to be used. Repeat step 6, 7, 8 and 9 by replacing (d_1, d_2, d_3) by (d_2, d_3, d_4) and find the new C_k and call it C'_k.

11) Search for common rows in C_k and C'_k. In real cases in which there are propagation model errors, sometimes there are not any crossing point. Instead the points are near to each other. Thus a bound has to be defined for recognizing the neighbor points. If a unique position for access point is found, the algorithm ends. If not go to step 1.

V. Simulation Results

The algorithm is numerically tested to measure its capabilities. The following procedure is applied to employ the algorithm effectively.

First the position of access point (x_t, y_t) is selected randomly. The position of the first point (x_1, y_1) is selected as the reference point and set to $(0, 0)$. Its relative distance l_1 and direction θ_1 from the second point (x_2, y_2) is selected randomly. Then the position of (x_2, y_2) is calculated and its relative distance l_2 and direction θ_2 from the third point (x_3, y_3) is selected by random. Having (x_1, y_1), (x_2, y_2), (x_3, y_3) and (x_t, y_t), the real distances d_1, d_2 and d_3 can be easily calculated.

In a real condition, the distances d_1, d_2 and d_3 are unknown and have to be determined in order to find the access point position. All the available data is relative positions of test points and their corresponding RSS values. Having d_1, d_2 and d_3, their corresponding RSS values are calculated from the proposed signal propagation model. These RSS values are considered as the data gathered from test points (RSS_1, RSS_2, RSS_3).

The proposed algorithm is then executed to find the access point position. The algorithm was implemented in MATLAB. Primitive results of simulation show that the proposed model and algorithm can together work to find the real position of the access point if the measurement error is small enough. Fig 5 shows the result for a sample case. In this case blue '*' points show calculated access point candidates considering M_1, M_2 and M_3 measurement points. In order to reduce access point candidates, the fourth measurement point M4 is added. Red '+' points show calculated access point candidates considering M_1, M_2 and M_4 and green '$\times$' points show calculated access point candidates considering M_1, M_3 and M_4. The position of access point can be considered at the center of neighborhood circle in which the points of different colors are sufficiently near each other. The figure shows the overall result is acceptable and the position of access point can be found. For larger amounts of measurement error and more complicated cases the algorithm must be modified to include more measurements.

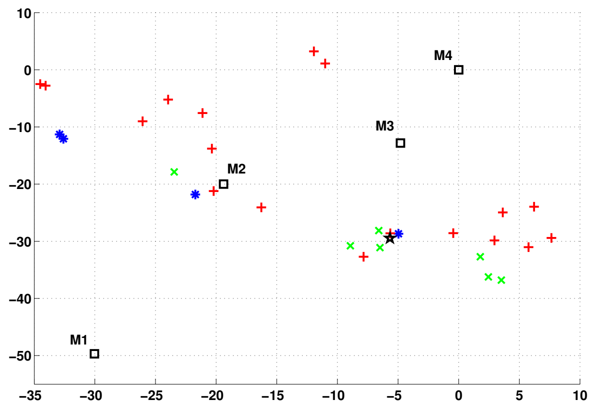

Fig. 5: A sample case of simulation results - Black squares are measurement points. The black star shows the real position of access point. Blue, red and green points represent the candidates for access point position

Benefits of this method are easy manipulation and implementation, no mathematical complexity, and applicabality in new ideas and applications: most Devices like smart phones and tablets have built-in WiFi modules and sensors like accelerometer and compass, hence this method can be implemented on these devices.

VI. Conclusions

In this paper, a non-monotonic signal propagation model for an indoor environment is presented. This model, along with a modified triangulation algorithm that needs received signal strength values, relative distance and directional information, is used for access point position estimation. Then by these information and an arbitrary reference point, the relative location of access points is found. The proposed algorithm has no mathematical complexity and can be easily implemented. Simulation results confirm that the proposed algorithm could be of practical use. As most smart phones and tablets have WiFi modules and sensors like accelerometer and compass hence this method can be implemented on these devices too. Further works including implementation of the proposed algorithm on a smart phone and developing the algorithm for more complex indoor environments that have many barriers is needed.

References

[1] IEEE-SA -IEEE Get 802 Program - 802.11: Wireless LANs. [Online]. Available: *http://standards.ieee.org/about/get/802/802.11.html.* [Accessed: 08-Dec-2012].

[2] H. Liu, H. Darabi, P. Banerjee, and J. Liu, "Survey of Wireless Indoor Positioning Techniques and Systems," *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews,* vol. 37, no. 6, pp. 1067 1080, Nov. 2007.

[3] Y. Kim, Y. Chon, and H. Cha, "Smartphone-Based Collaborative and Autonomous Radio Fingerprinting," *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews,* vol. 42, no. 1, pp. 112 122, Jan. 2012.

[4] M. Quan, E. Navarro, and B. Peuker, "Wi-Fi Localization Using RSSI Fingerprinting," *Computer Engineering,* Jan. 2010.

[5] T. K. Sarkar, M. C. Wicks, M. Salazar-Palma, and R. J. Bonneau, *Smart Antennas.* 2005.

[6] K. Pahlavan and A. H. Levesque, *Wireless Information Networks,* 2nd ed. Wiley, 2005.

[7] K. Curran and E. Furey, "Pinpointing users with location estimation techniques and Wi-Fi hotspot technology," *Int. J. Netw. Manag.,* vol. 18, no. 5, pp. 395408, Sep. 2008.

[8] B. Bittins and J. Sieck, "Multisensor and Collaborative Localization for Diverse Environments," *Computer Modeling and Simulation, UKSIM European Symposium on,* pp. 406411, 2011.

[9] D. Tassetto, E. H. Fazli, and M. Werner, "A novel hybrid algorithm for passive localization of victims in emergency situations," *International Journal of Satellite Communications and Networking,* vol. 29, no. 5, pp. 461478, 2011.

[10] K. Kikuchi, Y. Murata, G. Chakraborty, T. Takayama, and N. Sato, "Location Information System for Access Points in the Heterogeneous Wireless Enviornment," *in Proceedings of the 2012 26th International Conference on Advanced Information Networking and Applications Workshops,* Washington, DC, USA, 2012, pp. 538543.

[11] Y. Liu, Q. Wang, J. Liu, and T. Wark, "MCMC-based indoor localization with a smart phone and sparse WiFi access points," in *2012 IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOM Workshops)*, 2012, pp. 247 252.

[12] M. M. Atia, M. J. Korenberg, and A. Noureldin, "Particle-Filter-Based WiFi-Aided Reduced Inertial Sensors Navigation System for Indoor and GPS-Denied Environments," *International Journal of Navigation and Observation,* vol. 2012, pp. 112, 2012.

[13] H. Vathsangam, A. Tulsyan, and G. S. Sukhatme, "A Data-Driven Movement Model for Single Cellphone-Based Indoor Positioning," in *2011 International Conference on Body Sensor Networks (BSN),* 2011, pp. 174 179.

[14] J. Koo and H. Cha, "Unsupervised Locating of WiFi Access Points Using Smartphones," *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews,* vol. PP, no. 99, pp. 1 13, 2012.

[15] T. F. Cox and M. A. A. Cox, *Multidimensional Scaling,* Second Edition. Taylor & Francis Group, 2001.