RSS-Based Indoor Positioning with Weighted Iterative Nonlinear Least Square Algorithm

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***Abstract*— In recent years, researches on indoor positioning have become one of the most studied subject. This paper presents a real-time Wi-Fi-based indoor localization system using 2.4 GHz Wi-Fi signals. This experiment consists of two main phases. In the first phase, establishing a relationship between the received signal strength and the distance via signal propagation model, the distances between the mobile devices and the access points were determined using the log-distance path loss model. In the second stage, to test the usability and the performance of weighted iterative nonlinear least square algorithm for Wi-Fi based indoor positioning application, coordinates of the mobile device were estimated using this algorithm. This system runs on mobile devices in real time at line-of-sight indoor environments.**

Keywords - Indoor positioning; RSS; signal propagation model; weighted least square; Wi-Fi; 2.4 GHz.

I. INTRODUCTION

In recent years, academic and commercial studies on indoor positioning that have focused on producing real-time, and accurate location information has become one of the important investigation issues [1]. In the outdoor environments, sufficient 3D positioning accuracies can be obtained using Global Navigation Satellite Systems (GNSS) [2]. However, GNSS signals are losing its influence due to various reasons, such as multipath and reflection in indoor environments. Therefore, the accuracy obtained in outdoors environments can't be achieved in indoor environments using GNSS. In recent years, in order to obtain the desired positioning accuracy in indoor areas, many studies have been conducted using different technologies such as GNSS [3], Ultra-Wide Band (UWB) [4], Radio Frequency Identification (RFID) [5], Infrared (IR), Bluetooth [6] and Wireless Local Area Network (WLAN) [7]. Among these technologies, WLAN stands out because of using the pre-existing Wi-Fi infrastructure within buildings, and also Wi-Fi signals can be received by smartphones and tablets. So, WLAN-based indoor localization does not require any additional cost or hardware. Therefore, WLAN-based indoor localization has been frequently investigated in recent years.

Various classifications in many studies have been made for indoor positioning system. One of these classifications has been made depending on the distances named as rangeless and the range-based classification [8]. Rangeless algorithms are working regardless of the distance. Range-based location algorithms determine the location of the mobile device using the distances from the reference devices. Range-based algorithms are classified as Received Signal Strength (RSS), Angle of Arrival (AOA), Time of Arrival (TOA), and Time Difference of Arrival (TDOA) [9]. TOA, TDOA and AOA algorithms require dedicated equipment to perform the distance and angle measurements, so they require additional costs [10]. However, RSS-based algorithms require no additional hardware or cost.

In the literature, RSS-based indoor positioning is divided into two different approaches named as fingerprinting and propagation model-based [11]. The Fingerprinting approach consists of two phases named as offline and online phases. In the offline phase, a radio-map is created in the workspace using the signal strength values received from all Access

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Points (APs). In the online phase, the position of the device is established by matching the RSS values that of the offline phase. The major drawback of this approach is requires more labor during the offline phase measurements. The Propagation model-based approach consists of two phases. In the first phase, distances between the mobile device and APs are determined using signal propagation models and in the second phase, the mobile device's position is determined using three or more distances with positioning algorithms [12], such as Trilateration, Least Squares, Extended Kalman Filter, etc. Such distances can be determined by performing special applications in the workspace or obtained using predetermined signal propagation models without requiring any additional applications such as the ITU Path loss model [ITU] proposed by the International Communication Union and Log-distance path loss model and etc. RSS signals are affected by external factors in indoor environments such as fading, diffraction and multipath, so the distance estimation stage is one of the most critical phases for RSS-based indoor positioning applications [13].

In this study, a RSS-based indoor positioning study has been conducted at a direct line-of-sight indoor environment. The Log-distance path loss model used to determine the distances between the mobile device and APs and the position of the mobile device was established using the weighted iterative nonlinear least square method (WINLSQ). Positioning accuracy of the used method was tested experimentally at 27 different points.

The outline of the paper is arranged as follows. Section 2 formulates the distance estimation stage using signal propagation model, and positon estimation of the mobile device using WINLSQ is described in Section 3. Section 4 describes the study area and evaluates experimental results, and finally, the conclusion of the paper is presented in Section 5.

II. SIGNAL PROPAGATION MODEL

The ranges between the mobile devices and APs are usually estimated through RSS signals due to ease of implementation and not requiring any additional costs [14]. Signal propagation models are used to obtain RSS-based ranges. RSS are affected by environmental conditions depending on obstacles, multipath, scattering, reflection, shadowing and diffraction in indoor areas [15]. So, ranges obtained using the RSS can include large range errors, and this directly affects the accuracy of the position estimation.

Signal strength decreases logarithmically depending on the distance [16]. To model the relationship between the distance and RSS in the indoor or outdoor environments, many signal propagation models have been proposed. Due to its ease of use, log-distance path loss model is mostly used in the literature [17].

Log-distance path loss model is represented in the following equations [15-16]:

$$PL(dB) = PL(d_0) + 10n\log_{10}\left(\frac{d}{d_0}\right) + X_\sigma \tag{1}$$

$$PL(d_0) = -20\log_{10}\lambda + 20\log_{10}(4\pi) + 20\log_{10}(d_0) \tag{2}$$

where, $PL(d_0)$ is the path loss at the reference distance, n is the path loss exponent depends heavily on the studied indoor environment and building type, d is the distance between the receiver and the transmitter in meters, d_0 is the reference distance in meters usually chosen as 1 meter, X_σ is the Gaussian random variable with zero mean and standard deviation of σ dB, and λ is the wavelength of the signal in meters.

III. WEIGHTED ITERATIVE NONLINEAR LEAST SQUARE ALGORITHM

Minimizing the square error, linear and non-linear parameters can be estimated using least square algorithms [8]. In the absence of variance information, non-linear parameter estimation can be accepted [18]. The solution of non-linear least square needs linearization using a few algorithms, such as the Taylor series.

In the literature, many least square algorithms are used to solve the positioning problem for indoor localization problem. In this study, we use the WINLSQ algorithm that is proposed in [19]. In this algorithm, the observation model is given as;

$$z = h(x) + v \tag{3}$$

where, z is the measurement vector, and the function of the state vector x is represented by $h(x)$. The equation (4) can be obtained with the linearization of the nonlinear measurement vector around the current state estimation $\hat{x}$ [20].

$$z = h(\hat{x}) + H\delta x + v \tag{4}$$

where, the innovation of the state vector is presented as:

$$\delta x = x - \hat{x} \tag{5}$$

and, design matrix is represented as:

$$H = \frac{dh(x)}{dx} \tag{6}$$

The measurement misclosure vector δz can be obtained by rearranging the equation (4):

$$\delta z = H\delta x + v \tag{7}$$

The solution (8), covariance matrix of the solution (9) and new state vector (10) are given respectively as:

$$\delta\hat{x} = (H^T R^{-1} H)^{-1} H^T R^{-1} \delta z \tag{8}$$

$$C_{\delta\hat{x}} = (H^T R^{-1} H)^{-1} \tag{9}$$

$$\hat{x}_{updated} = \hat{x} + \delta\hat{x} \tag{10}$$

where, R is the observation covariance matrix. The iteration of this process continues until $|\delta\hat{x}| < threshold$. The residual vector (11) and its covariance matrix (12) are given as follows:

$$r = z - h(\hat{x}) \tag{11}$$

$$C_r = R - H(H^T R^{-1} H)^{-1} H^T \tag{12}$$

IV. EXPERIMENTAL RESULTS

This experiment consists of two main phases, distance estimation using the Log-distance path loss model and position estimation using WINLSQ. To assess the performance of this system, a static test is conducted at 27 different points (named as observed points) in the application area. Four similar ASUS DSL-AC68U APs are placed in the corners of the application area that is 10 m x 9.6 m at line-of-sight indoor environment. In Fig. 1, red and green points indicate the locations of APs and the observed points, respectively, in the experimental area. Two dimensional geodetic coordinates of APs and the observation points were determined accurately using the total station, and that is accepted as the reference coordinates. Simultaneously transmitted 2.4 GHz Wi-Fi signals (IEEE 802.11ac) from the APs were collected by a Samsung Note 5 mobile device that has an Android operating system. These signals were converted into distances using the Log-distance path loss model, and the position of the 27 observed points were estimated using the WINLSQ algorithm. JAVA programming language was used with the JAMA basic linear algebra package to make all the calculations. The data was collected 150 times at all of the observation points, and the coordinates of these points was obtained using the mentioned algorithms in real time by mobile device. The differences between the obtained coordinates and the known coordinates, and the mean value of the differences are depicted in Fig. 2.

According to the values in Fig. 2, the positioning error values are varying between 0.81-13.16 m. Mean values of these errors is 3.73m, and standard deviation of the errors are 2.37 m. While errors of 26 observed points are up to 7.13 m, exceptionally only the 22th point's positioning error is more than 8 m. This is the reason that huge RSS fluctuations received from AP-2 and AP-3 during the measurement of 27th point. These values were tested with the χ^2 test, and they passed the test successfully at a 95% confidence level.

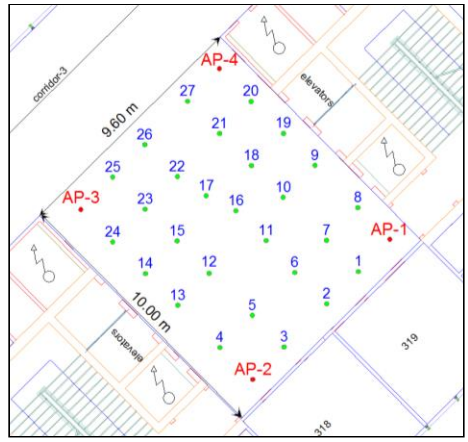

Figure 1.Experimental area

V. CONCLUSIONS

In this paper, we examined the usability of the weighted iterative nonlinear least square algorithm in a 2.4 GHz Wi-Fi based indoor environment to find the position of the mobile device. The relationship between the distance and RSS was determined using log-distance path loss model via received signals strength. Weighted iterative nonlinear least square algorithm was adopted for estimation of the position.

Obtained results indicated that 92 percent of the error values were smaller 5 meter. Although, these results are enough for many indoor positioning applications, some error values are still very huge. It is clear that this situation emerges from the fluctuations of the RSS values. In order to eliminate this fluctuation, raw signal values have been filtered using other algorithms before finding the distances.

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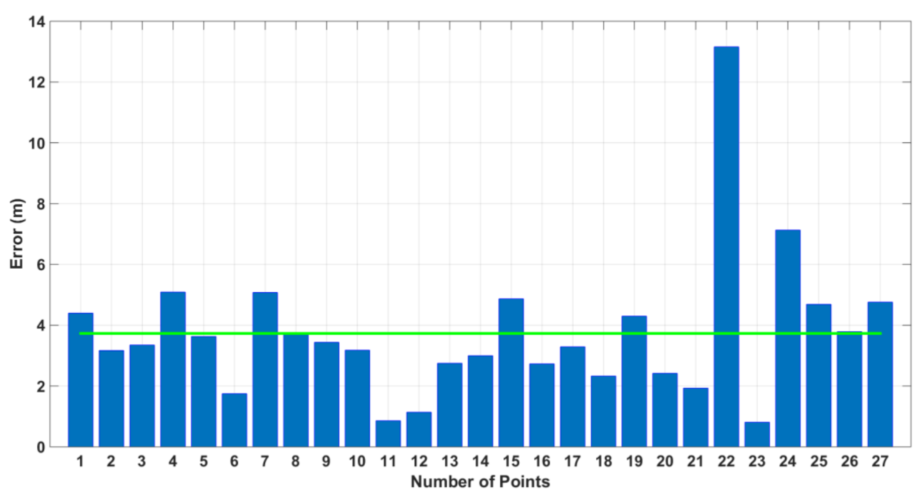

Figure 2. The differences between reference and estimated coordinates are shown as the blue bars and mean value of differences are shown as the green line.

REFERENCES

[1] J. Yim, S. Jeong, K. Gwon, and J. Joo, "Improvement of Kalman Filters for WLAN based Indoor Tracking," Expert Systems with Applications, vol.37, pp.426-433, 2010, doi:10.1016/j.eswa.2009.05.047.

[2] J. Wang, R. V. Prasad, X. An, and I. G. M. M. Niemegeers, "A study on wireless sensor network based indoor positioning systems for context-aware applications," Wireless Communications and Mobile Computing, vol. 12, issue. 1, pp. 53-70, 2012.

[3] I. Selmi, and N. Samama, "Indoor positioning with GPS and GLONASS-like signal use of new codes and a repealite-based infrastructure in a typical museum building," annals of telecommunications, vol. 69, pp. 641-655, 2014, doi: 10.1007/s12243-014-0422-y.

[4] C. Basaran, J. Yoon, S. H. Son, and T. Park, "Self-Configuring Indoor Localization Based on Low-Cost Ultrasonic Range Sensors," Sensors, vol.14, pp.18728-18747, 2014, doi:10.3390/s141018728.

[5] L. Geng, M. F. Bugallo, A. Athalye, and P. M. Djurić, "Indoor Tracking With RFID Systems," IEEE Journal of Selected Topics in Signal Processing, vol. 8, no. 1, pp. 96-105, February 2014, doi: 10.1109/JSTSP.2013.

[6] C. Liang, et al., "Bayesian Fusion for Indoor Positioning Using Bluetooth Fingerprints," Wireless Personal Communications, vol. 70, pp. 1735-1745, 2013, doi:10.1007/s11277-012-0777-1.

[7] J. Yim, "Development of Web Services for WLAN-based Indoor Positioning and Floor Map Repositories," International Journal of Control and Automation, vol.7, no.3, pp.63-74, 2014, doi:10.14257/ijca.2014.7.3.07.

[8] H. Li, "Low-Cost 3D Bluetooth Indoor Positioning with Least Square," Wireless Personal Communications, vol.78, no.2, pp.1331-1344, 2014, doi: 10.1007/s11277-014-1820-1.

[9] R. Khan, S. U. Khan, S. Khan, and M. U. A. Khan, "Localization Performance Evaluation of Extended Kalman Filter in Wireless Sensor Networks," Procedia Computer Science, vol. 32, pp. 117-124, 2014.

[10] P. Tarrio, A. M. Bernardos, J. A. Besada and J. R. Casar, "A new positioning technique for RSS-Based localization based on a weighted least squares estimator," 2008 IEEE International Symposium on Wireless Communication Systems, Reykjavik, pp. 633-637, 2008, doi: 10.1109/ISWCS.2008.4726133.

[11] M. A. Al-Ammar, et al., "Comparative Survey of Indoor Positioning Technologies, Techniques, and Algorithms," Cyberworlds (CW), 2014 International Conference on, Santander, pp. 245-252, 2014.

[12] J. Cota-Ruiz, J. G. Rosiles, E. Sifuentes, and P. Rivas-Perea, "A Low-Complexity Geometric Bilateration Method for Localization in Wireless Sensor Networks and Its Comparison with Least-Squares Methods," Sensors, vol. 12, pp. 839-862, 2012.

[13] R. Khan, F. Sottile, and M. A. Spirito, "Hybrid Positioning through Extended Kalman Filter with Inertial Data Fusion," International Journal of Information and Electronics Engineering, vol. 3, no. 1, pp. 127-131, January 2013.

[14] J. Koo and H. Cha, "Localizing WiFi Access Points Using Signal Strength," IEEE Communications Letters, vol. 15, no. 2, pp. 187-189, February 2011, doi: 10.1109/LCOMM.2011.121410.101379

[15] J. S. Seybold, "Introduction to RF Propagation," 1th ed., vol. 1, John Wiley&Sons:USA, 2005, pp. 210-217.

[16] T. S. Rappaport, "Wireless Communications: Principles and Practice," Prentice Hall PTR, Upper Saddle River, NJ, 2001.

[17] F. Xiao, M. Wu, H. Huang, R. Wang, and S. Wang, "Novel Node Localization Algorithm Based on Nonlinear Weighting Least Square for Wireless Sensor Networks," International Journal of Distributed Sensor Networks, vol. 2012, Article ID 803840, 6 pages, 2012, doi:10.1155/2012/803840.

[18] W. Wang, H. Ma, Y. Wang, and M. Fu, "Performance analysis based on least squares and extended Kalman filter for localization of static target in wireless sensor networks," Ad Hoc Networks, vol. 25, part A, pp. 1- 15, February 2015.

[19] Y. Zhuang, Z. Syed, J. Georgy, and N. El-Sheimy, "Autonomous smartphone-based WiFi positioning system by using access points localization and crowdsourcing," Pervasive and Mobile Computing, vol. 18, pp. 118-136, April 2015, doi: http://dx.doi.org/10.1016/j.pmcj.2015.02.001.

[20] Y. Zhuang, B. Wright, Z. Syed, Z. Shen, and N. El-Sheimy, "Fast WiFi access point localization and autonomous crowdsourcing," Ubiquitous Positioning Indoor Navigation and Location Based Service (UPINLBS), 2014, Corpus Christ, TX, pp. 272-280, 2014, doi: 10.1109/UPINLBS.2014.