A Review on Indoor Localization Techniques using Received Signal Strength

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Abstract. This paper opens with an introduction to the term localization techniques using RSS. The study contains concepts, requirements and specifications for each category of techniques. The paper also presents pros and cons for investigated localization techniques and conducts comparisons between them.

Keywords: Indoor Localization, Received Signal Strength, Radio-Frequency Fingerprinting, Least Square Technique.

1. Introduction

The main target of localization is to make a monotonic relationship between the object location and it's corresponding RSS [1]. RSS level tend to fall-off as the distance between sensors increases. However, RSS-distance relationship is not necessarily to be linear especially in indoor environments due to the effect of multipath [2]. Moreover, as half of our bodies is water, people movement cause fluctuations of RSS with time which reduce localization accuracy [3-5].

RSS measuring requires only power detectors which are available in WLAN, UWB, Zigbee, Bluetooth and infrared devices. Utilizing WLAN for localization purposes is advantageous due to its continuous surveillance, affordable and its ability of operating unattended for years [6, 7]; however this may cause interference difficulties with microwave ovens and Bluetooth devices, since these devices operate on the same frequency bands, however using different channels will minimize the correlation [2].

RSS systems do not rely on timing information, this makes them more robust to multipath. Moreover, synchronization between devices is not required [8]. RSS localization systems excel in short-range distances, however, it provides lower accuracy in long-range distances comparing to TOA systems which are favourable for outdoor applications [9].

On the other hand, training and complex matching algorithms are needed to perform localization [10]. Moreover, RSS is sensitive to shadowing, low signal to noise ratio (SNR), and NLOS propagation.

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2. RSS-Based Localization Algorithms

Many RSS-based localization algorithms are presented in literature including range-based position, radiofrequency fingerprinting technique, proximity-based position and probabilistic estimation [11], a brief discussion on these algorithms are introduced in the following subsections.

2.1 Range-based position

Localization using range-based techniques include two stages: *ranging* and *lateration* [12], in the first stage a distance-power relationship is formulated depending on the observed RSS values, in the latter step mobile's location is inferred based on the distances obtained using *least square techniques.* Using this type of localization is preferred due to its ease; however, it suffers from varying RSS measurements [13].

RSS values vary in a random manner within indoor environments. As the Tx-Rx distance increases, the SS level does not follow a monotonic decrease. **Figure 1** shows Tx-Rx distance relationship with RSS along a building hallway.

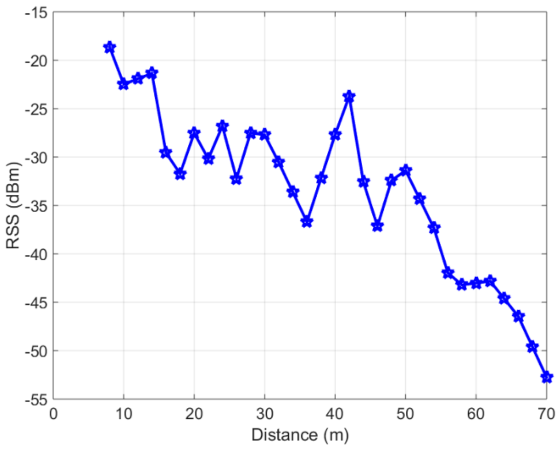

Fig. 1. Attenuation of RSS within a hallway.

The figure shows a nonlinear relationship between RSS and Tx-Rx distance, this nonlinearity arises due to the fading effect. At any receiver point, the received power is the transmitted power from transmitter minus losses; those losses are due to distance (the area mean propagation loss), shadowing (local mean propagation loss) and multipath (fast fading). In indoor environments access points (AP) locations tend to be known while the mobile's location is unknown. For AP located at a known location (x_i, y_i) and a mobile located at an unknown location (x, y), the received power at the mobile is given by Equation 1 [11, 14]:

$$P(d_i) = P_0 - 10n\log_{10}\left(\frac{d_i}{d_0}\right) + \chi_\sigma \qquad (1)$$

where d_i is the distance between i^{th} AP and the mobile, $(P_0 = P_t + \overline{PL}(d_0))$ is the RSS recorded at reference distance, it's calculated experimentally or by applying Equation 2, P_t is the transmitted power, $\overline{PL}(d_0)$ is the average path loss at reference distance (usually 1 m) and χ_σ is a Gaussian random variable with zero mean represents shadow fading.

$$P_0 = P_t\left(\frac{\lambda}{4\pi d_0}\right)^2 \tag{2}$$

Solving Equation 1 for d_i gives the distance between AP and the mobile:

$$d_i = d_0\left[10^{\frac{P(d_i)-P_0+\chi_\sigma}{10}}\right]^{\frac{-1}{n}} \tag{3}$$

For an omnidirectional antenna, mobile possible locations may lie on a circle, mobile coordinates are the solution of the circle equation shown below:

$$d_i{}^2 = (x-x_i)^2 + (y-y_i)^2 \tag{4}$$

Provided that d_i value is given by applying Equation 3. Since d_i and (x_i, y_i) are known, the remaining unknowns are (x, y), which needs at least another equation to be solved; however, with two equations there will be two possible solutions, in order to have a unique solution three equations are required, the intersection of these equations will determine the location of the mobile as shown in **Figure 2**, if the problem is in 3D (x, y, z) then four APs are used at least to have unique solution [15].

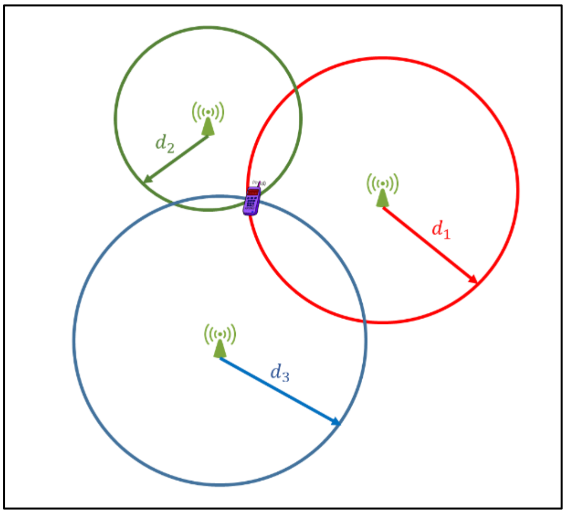

Fig. 2. Trilateration localization.

Estimation of environmental parameters χ_σ and n is accomplished by taking a training data (SS collected from known locations), by fitting these data into a model using *linear regression* the unknown parameters are estimated [16].

Least Square Technique

Due to the effect of noise and NLOS, the exact solution for a mobile's location may not exist. In this case, least-square methods are applied. These methods are categorized into *Non-linear least square* (NLS) and *linear least square* (LLS)[11]. The principle is as follows: the available information includes *known* parameters (x_i, y_i) and the *measured* parameter d_i. The target to estimate is the *unknown* location of the sensor (x, y). This is accomplished by searching for all possible locations $(\hat{x}, \hat{y})$ such that the distance between this point and (x_i, y_i) is approaching d_i as much possible for all N APs, as shown in Equation 5 [11]:

$$(\hat{x}, \hat{y}) = \arg\min_{x,y} \sum_{i=1}^{N} \left[(x - x_i)^2 + (y - y_i)^2 - {d_i}^2\right] \tag{5}$$

The above approach is the NLS method, which depends on its initial guess, therefore it's required to perform several iterations in order to get better results; however, this requires huge computations. For a less computational cost, LLS approach is performed; nevertheless less accurate results are obtained [11].

A possible way to perform linearization is by taking the mean of all APs measurements then perform a subtraction from each observation [11].

$$\frac{1}{N}\sum_{i=1}^{N}[(x - x_i)^2 + (y - y_i)^2] = \frac{1}{N}\sum_{i=1}^{N} {d_i}^2 \tag{6}$$

The K[th] AP measurement becomes:

$$\begin{aligned} &\left[y_k - \frac{1}{N}\sum_{i=1}^{N} y_i\right] y + \left[x_k - \frac{1}{N}\sum_{i=1}^{N} x_i\right] x \\ &= 0.5\left(\left[{y_k}^2 - \frac{1}{N}\sum_{i=1}^{N} {y_i}^2\right] + \left[{x_k}^2 - \frac{1}{N}\sum_{i=1}^{N} {x_i}^2\right] - \left[{d_k}^2 - \frac{1}{N}\sum_{i=1}^{N} {d_i}^2\right]\right) \end{aligned} \tag{7}$$

For all N-APs, a matrix can be formed as ($\boldsymbol{Az} = \boldsymbol{b}$) where ($\boldsymbol{z} = \begin{bmatrix} y \\ x \end{bmatrix}$)

$$\boldsymbol{A} = \begin{pmatrix} y_1 - \frac{1}{N}\sum_{i=1}^{N} y_i & x_1 - \frac{1}{N}\sum_{i=1}^{N} x_i \\ \vdots & \\ y_N - \frac{1}{N}\sum_{i=1}^{N} y_i & x_N - \frac{1}{N}\sum_{i=1}^{N} x_i \end{pmatrix} \tag{8}$$

$$\boldsymbol{b} = \begin{pmatrix} 0.5\left(\left[{y_1}^2 - \frac{1}{N}\sum_{i=1}^{N} {y_i}^2\right] + \left[{x_1}^2 - \frac{1}{N}\sum_{i=1}^{N} {x_i}^2\right] - \left[{d_1}^2 - \frac{1}{N}\sum_{i=1}^{N} {d_i}^2\right]\right) \\ \vdots \\ 0.5\left(\left[{y_N}^2 - \frac{1}{N}\sum_{i=1}^{N} {y_i}^2\right] + \left[{x_N}^2 - \frac{1}{N}\sum_{i=1}^{N} {x_i}^2\right] - \left[{d_N}^2 - \frac{1}{N}\sum_{i=1}^{N} {d_i}^2\right]\right) \end{pmatrix} \tag{9}$$

The mobile location can be estimated as:

$$z = (A^T A)^{-1} A^T b \tag{10}$$

Lateration is prone to outliers (the estimated position is extremely distant from the actual one), in order to give robustness to the system, outliers measurements are excluded by taking the median value of the sum [17]:

$$(\hat{x}, \hat{y}) = \arg\min_{x,y} median_i \sum_{i=1}^{N} \left[(x - x_i)^2 + (y - y_i)^2 - {d_i}^2\right] \tag{11}$$

Differential RSS (DRSS)

Equation 1 can be expressed in normalized form as:

$$P_i = P(d_i) - P_0 = -10n \log_{10}\left(\frac{d_i}{d_0}\right) + \chi_\sigma \tag{12}$$

As can be seen from Equation 1 or 12 measurements accuracy depend on many parameters including the unknown P_t, another problem is the fluctuation of RSS values with time. In order to remove the need for having a priori knowledge of P_t and to reduce the effects of environmental changes, Differential RSS (DRSS) is adopted [18, 19].

$$P_{ij} = P_i - P_j = 10n \log_{10}\left(\frac{d_j}{d_i}\right) + \chi_{\sigma_{ij}} \tag{13}$$

where ($\chi_{\sigma_{ij}} = \chi_{\sigma_i} - \chi_{\sigma_j}$). P_i and P_j have a variance of σ^2, P_{ij} have a variance of $2\sigma^2$ [16]. Generally, if m APs are collaborating in localization there will be ($\frac{m(m-1)}{2}$) formulated DRSS equations, among these equations ($m - 1$) are basic equations, while the rest are redundant, the solution of each basic equation will lie on a hyperbola, the intersection of these hyperbolas gives the mobile's coordinates [20].

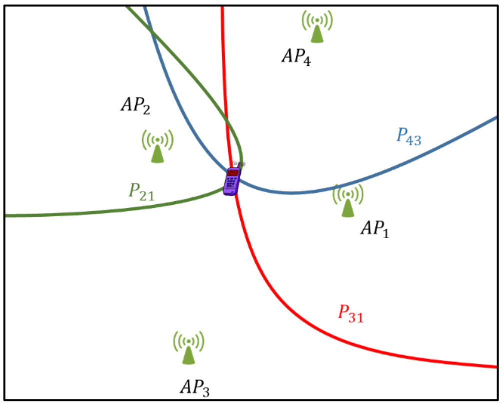

Fig. 3. Hyperbolic localization using DRSS.

For example, using 3 APs system, there will be 2 basic equations (P_{21} and P_{31}) while (P_{32}) is a linear combination of (P_{21} and P_{31}), in order to have a unique solution three basic equations are required which is achieved by adding another AP in **Fig. 3**. The generated basic equations are (P_{21}, P_{31} and P_{43}), while (P_{41} and P_{42}) are a linear combination of the basic function ($P_{43} - P_{31}, P_{43} - P_{32}$) respectively.

Although this method reduces dependence on knowing the value of P_t, it has poor performance in indoor environments compared to RSS [19].

2.2 Radio-Frequency Fingerprinting

Constructing a signal propagation model can be a very challenging task due to complexities of indoor environments, rather than modelling RSS behaviour another approach can be used known as Radio Frequency-fingerprinting technique [7, 21, 22].

RF–fingerprinting involves of two stages; the offline stage and the online stage. In the offline stage (Training phase) the area of interest is divided into grids, in each grid, many RSS are scanned from nearby APs and averaged to remove the fast fading effect, averaged RSS with corresponding location (also called *reference points* RP) are stored in a database known as *Radio map* [23].

In Online stage (Real-time phase) RSS measurements are collected from unknown locations called *test points* (TP), these measurements are then compared with the database built in the offline phase. One popular approach is to find the smallest Euclidean distance between the test point measurements and the radio map database [24]. The RP whose Euclidean distance with TP is the smallest represents the nearest location to TP [23].

$$\arg\min_{RP(k)} \sqrt{\sum_{l=1}^{L} (TP_l - RP(k)_l)^2} \ \forall\ \mathrm{k} = 1{:}\,\mathrm{K} \tag{14}$$

where k is the k^{th} RP. Other approaches estimate the k-nearest positions by finding lowest values of Equation 14 [25].

The level of achieved accuracy depends heavily on how many APs and RPs used. Adding more APs will reduce the possibility of having ambiguous results and tend to enhance the localization process. Adding more RPs will enhance resolution; however, this will cost more labour work. Another disadvantage of this approach is the need for regular updates for the radio map as the building layout or the number of operating APs may be changed [11, 26]. **Fig. 4** shows the distribution of APs, RPs and TPs.

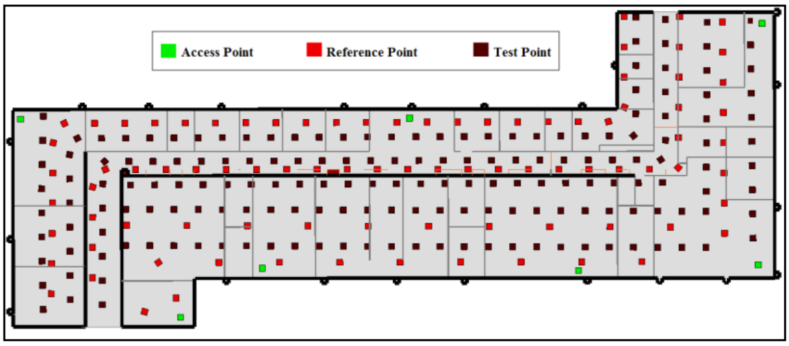

Fig. 4. RF-fingerprinting approach

2.3 Proximity-based position (Free Range Localization)

Proximity measurements (relative positioning) have been suggested as a cheap and simple mean to estimate the range between mobile and AP location.

In contrast to range-based localization which suffers from the fading differences in the propagation channel, proximity approach does not matter if the mobile and the AP are exposed to same fading channel or not, as long as they are within communication range [27].

Mobile's location is estimated using the coordinates of the AP. Proximity approach is simple and widely used, however, accuracy is limited to AP radio coverage [28].

2.4 Maximum Likelihood Estimation

In this method RSS behaviour is modelled as a random variable, two stages are performed similarly to RF-Fingerprinting approach. In the first stage, SS measurements are collected from the area of interest, these data are processed to give a probabilistic distribution for the SS behaviour in each location, in the second stage mobile's RSS from surrounding APs are collected from unknown location and stored in vector and then mobile's location is inferred based on Maximum Likelihood Estimation (MLE) as shown in Equation 15 [29]:

$$(\hat{x}, \hat{y}) = \arg\max_{L_j} \left(P\left(L_j | \boldsymbol{ss}\right) \right) \tag{15}$$

where $P\left(L_j|\boldsymbol{ss}\right)$ is the probability that the mobile is located at the location L_j given that the RSS vector is ($\boldsymbol{ss}$).

In the first stage, the study area is divided into grids, in each grid, the signal strength is measured from each AP extensively. If we assume a 4-grids environment with one AP, where many measurements were taken in each. At each grid the probability distribution of RSS from AP-1 $P(ss^j)$ will follow certain behaviour as seen in **Fig. 5**. This distribution also can be considered as the probability of having ss at grid j ($P\left(ss|L_j\right)$).

$$P(ss^j) = P\left(ss|L_j\right) \tag{16}$$

where j=1:4. The probability for RSS from AP-1 in all grids will be:

$$P(ss) = \frac{1}{4}\sum_{j=1}^{4} P(ss^j) \tag{17}$$

If we have M-APs then Equations 16 and 17 will be respectively:

$$P\left(\boldsymbol{ss}|L_j\right) = \prod_{i=1}^{M} P\left(ss_i|L_j\right) \tag{18}$$

$$P(\boldsymbol{ss}) = \prod_{i=1}^{M} P(ss_i) \tag{19}$$

In the localization stage, the question is given this level of RSS what is the probability for the mobile to be located in each grid? Or as shown in Equation 20 [29]:

$$P(L_j|\boldsymbol{ss}') = \frac{P(\boldsymbol{ss}'|L_j)P(L_j)}{P(\boldsymbol{ss})} \tag{20}$$

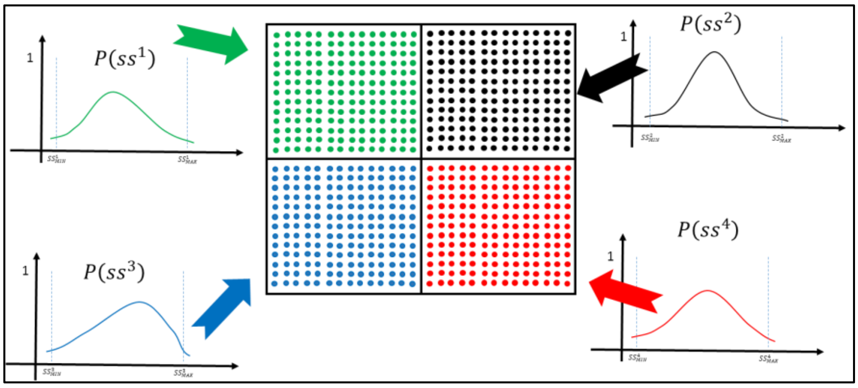

Fig. 5. Example of MLE RSS positioning methodology.

Since the location of the mobile is unknown, then the probability of each grid to be the location where the mobile locates is equal.

$$P(L_j) = \frac{1}{J} \tag{21}$$

The algorithm shows a precise analysis of the given data; however, it suffers from extensive labour work [11].

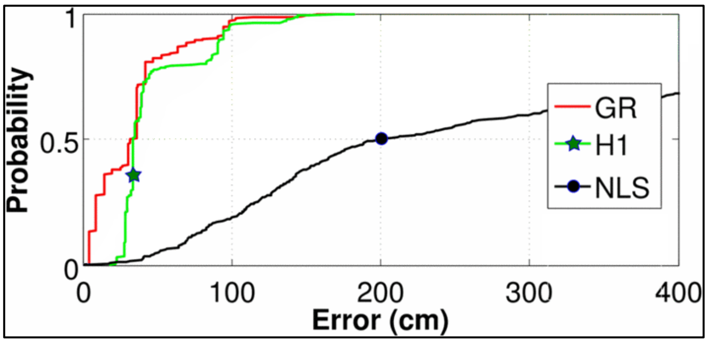

Fig. 6. Performance comparison between RSS based algorithms [30].

Fig. 6 and **Fig. 7** give comparisons between RSS based algorithm, including the radar algorithm (*RF-fingerprinting*), GR gridded radar (*RF-fingerprinting*), ABP (*MLE*), H1 (*MLE*), LLS and NLS (*Range based*) using WLAN network [11] [30], as seen in these figures, MLE and RF fingerprinting performance are very similar while for range-based algorithms the performance is relatively poor. Also, it can be seen that NLS is more accurate compared to LLS.

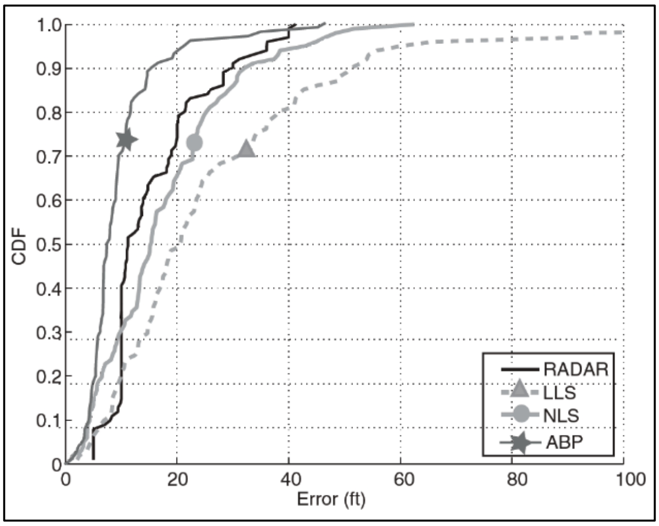

Fig. 7. Performance comparison between RSS based algorithms [11].

Conclusions

A study on indoor localization techniques using received signal strength (RSS) is introduced. The RSS is cheap as it requires only power detectors which are available in Wi-Fi, UWB, Zigbee, Bluetooth, and infrared devices, it does not require synchronization between devices, it also shows good performance in NLOS propagation scenarios; however, as the distance becomes larger accuracy degrades. Choosing the localization method depends on many factors including cost, available resources, type of environment and accuracy required; the most powerful technique is the one that gives high accuracy with less computation

References

[1] K. Sayrafian-Pour and D. Kaspar, "A robust model-based approach to indoor positioning using signal strength," in *Personal, Indoor and Mobile Radio Communications, 2008. PIMRC 2008. IEEE 19th International Symposium on*, 2008: IEEE, pp. 1-5.

[2] A. M. Ladd, K. E. Bekris, A. P. Rudys, D. S. Wallach, and L. E. Kavraki, "On the feasibility of using wireless ethernet for indoor localization," *IEEE Transactions on Robotics and Automation*, vol. 20, no. 3, pp. 555-559, 2004.

[3] Y. Chapre, P. Mohapatra, S. Jha, and A. Seneviratne, "Received signal strength indicator and its analysis in a typical WLAN system (short paper)," in *Local Computer Networks (LCN), 2013 IEEE 38th Conference on*, 2013: IEEE, pp. 304-307.

[4] L. Xu, F. Yang, Y. Jiang, L. Zhang, C. Feng, and N. Bao, "Variation of received signal strength in wireless sensor network," in *Advanced Computer Control (ICACC), 2011 3rd International Conference on*, 2011: IEEE, pp. 151-154.

[5] K. Ullah, I. V. Custodio, N. Shah, and E. dos Santos Moreira, "An Experimental Study on the Behavior of Received Signal Strength in Indoor Environment," in *Frontiers of Information Technology (FIT), 2013 11th International Conference on*, 2013: IEEE, pp. 259-264.

[6] H. Obeidat *et al.*, "Indoor localization using received signal strength," in *Design and Test Symposium (IDT), 2013 8th International*, 2013: IEEE, pp. 1-6.

[7] H.-S. Ahn and W. Yu, "Environmental-adaptive RSSI-based indoor localization," *Automation Science and Engineering, IEEE Transactions on*, vol. 6, no. 4, pp. 626-633, 2009.

[8] F. Bouchereau and D. Brady, "Bounds on range-resolution degradation using RSSI measurements," in *Communications, 2004 IEEE International Conference on*, 2004, vol. 6: IEEE, pp. 3246-3250.
[9] D. Munoz, F. B. Lara, C. Vargas, and R. Enriquez-Caldera, *Position location techniques and applications*. Academic Press, 2009.
[10] A. Hatami, K. Pahlavan, M. Heidari, and F. Akgul, "On RSS and TOA based indoor geolocation-a comparative performance evaluation," in *Wireless Communications and Networking Conference, 2006. WCNC 2006. IEEE*, 2006, vol. 4: IEEE, pp. 2267-2272.
[11] R. Zekavat and R. M. Buehrer, *Handbook of position location: Theory, practice and advances*. John Wiley & Sons, 2011.
[12] A. Savvides, H. Park, and M. B. Srivastava, "The n-hop multilateration primitive for node localization problems," *Mobile Networks and Applications,* vol. 8, no. 4, pp. 443-451, 2003.
[13] G. Zanca, F. Zorzi, A. Zanella, and M. Zorzi, "Experimental comparison of RSSI-based localization algorithms for indoor wireless sensor networks," in *Proceedings of the workshop on Real-world wireless sensor networks*, 2008: ACM, pp. 1-5.
[14] N. B. Priyantha, A. Chakraborty, and H. Balakrishnan, "The cricket location-support system," in *Proceedings of the 6th annual international conference on Mobile computing and networking*, 2000: ACM, pp. 32-43.
[15] K. Langendoen and N. Reijers, "Distributed localization in wireless sensor networks: a quantitative comparison," *Computer Networks,* vol. 43, no. 4, pp. 499-518, 2003.
[16] S. Mehdi Dehghan, H. Moradi, and S. A. Asghar Shahidian, "Optimal path planning for DRSSI based localization of an RF source by multiple UAVs," in *Robotics and Mechatronics (ICRoM), 2014 Second RSI/ISM International Conference on*, 2014: IEEE, pp. 558-563.
[17] D. Wagner, "Resilient aggregation in sensor networks," in *Proceedings of the 2nd ACM workshop on Security of ad hoc and sensor networks*, 2004: ACM, pp. 78-87.
[18] L. Lin, H.-C. So, and Y. T. Chan, "Accurate and simple source localization using differential received signal strength," *Digital Signal Processing,* vol. 23, no. 3, pp. 736-743, 2013.
[19] N. Chang, R. Rashidzadeh, and M. Ahmadi, "Robust indoor positioning using differential Wi-Fi access points," *Consumer Electronics, IEEE Transactions on,* vol. 56, no. 3, pp. 1860-1867, 2010.
[20] B.-C. Liu and K.-H. Lin, "Distance difference error correction by least square for stationary signal-strength-difference-based hyperbolic location in cellular communications," *Vehicular Technology, IEEE Transactions on,* vol. 57, no. 1, pp. 227-238, 2008.
[21] U. Alkasi, M. A. Shayokh, and H. P. Partal, "An experimental comparison study on indoor localization: RF fingerprinting and Multilateration methods," in *Electronics, Computer and Computation (ICECCO), 2013 International Conference on*, 7-9 Nov. 2013 2013, pp. 255-259, doi: 10.1109/ICECCO.2013.6718277.
[22] N. A. Khanbashi *et al.*, "Real time evaluation of RF fingerprints in wireless LAN localization systems," in *Positioning Navigation and Communication (WPNC), 2013 10th Workshop on*, 20-21 March 2013 2013, pp. 1-6, doi: 10.1109/WPNC.2013.6533273.
[23] L. Xie, Y. Wang, and X. Xue, "A new indoor localization method based on inversion propagation model," in *Wireless Communications Networking and Mobile Computing (WiCOM), 2010 6th International Conference on*, 2010: IEEE, pp. 1-4.
[24] P. Bahl and V. N. Padmanabhan, "RADAR: An in-building RF-based user location and tracking system," in *INFOCOM 2000. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE*, 2000, vol. 2: Ieee, pp. 775-784.
[25] D. Li, B. Zhang, Z. Yao, and C. Li, "A feature scaling based k-nearest neighbor algorithm for indoor positioning system," in *2014 IEEE Global Communications Conference*, 8-12 Dec. 2014 2014, pp. 436-441, doi: 10.1109/GLOCOM.2014.7036847.
[26] C. Feng, W. S. A. Au, S. Valaee, and Z. Tan, "Received-signal-strength-based indoor positioning using compressive sensing," *Mobile Computing, IEEE Transactions on,* vol. 11, no. 12, pp. 1983-1993, 2012.
[27] N. Patwari and A. O. Hero III, "Using proximity and quantized RSS for sensor localization in wireless networks," in *Proceedings of the 2nd ACM international conference on Wireless sensor networks and applications,* 2003: ACM, pp. 20-29.

[28] A. Küpper, *Location-based services: fundamentals and operation*. John Wiley & Sons, 2005.
[29] E. Elnahrawy, X. Li, and R. P. Martin, "The limits of localization using signal strength: A comparative study," in *Sensor and Ad Hoc Communications and Networks, 2004. IEEE SECON 2004. 2004 First Annual IEEE Communications Society Conference on*, 2004: IEEE, pp. 406-414.
[30] G. Chandrasekaran *et al.*, "Empirical evaluation of the limits on localization using signal strength," in *Sensor, Mesh and Ad Hoc Communications and Networks, 2009. SECON'09. 6th Annual IEEE Communications Society Conference on*, 2009: IEEE, pp. 1-9.