SHARF: A Single Beacon Hybrid Acoustic and RF Indoor Localization Scheme

Ahmed Zubair(✉), Zaid Bin Tariq, Ijaz Haider Naqvi, and Momin Uppal

School of Science and Engineering,
Lahore University of Management Sciences, Lahore, Pakistan
ahmedzubair2108@gmail.com, {ijaznaqvi,momin.uppal}@lums.edu.pk

Abstract. The inability of GPS (Global Positioning System) to provide accurate position in an indoor environment has resulted in global efforts for a precise indoor position system throughout the last decade. The current state of the art of localization and tracking estimates the position of the mobile node based on attributes like received signal strength (RSS), angle of arrival (AoA) etc. from at least three anchor nodes. This paper presents SHARF; a *single beacon* hybrid acoustic and RF localization scheme in an indoor environment. It combines the RF RSS information for ranging with the angle of azimuth from acoustic localization system based on beacon signals from only *one* target node to *one* anchor node. The experimental results show an improved localization accuracy in comparison to trilateration scheme. All these features, i.e. single beacon, hybrid approach and outlier rejection, posit the superiority of this technique over the existing systems.

Keywords: Indoor localization · Wireless acoustic sensor networks (WASN) · Received signal strength (RSS) · TIme difference of arrival (TDOA) · Angle of arrival (AOA)

1 Introduction

The developments in Global Positioning System (GPS) in the past two decades have revolutionized the way people commute and navigate. GPS, however, does not provide a reasonable position estimate in the indoor or cluttered environments due to high penetration losses, which stymies the reception of signals from at least 4 satellites. The success and utility of GPS has invoked quite an interest in the area of indoor localization among researchers. A right mix of accurate and robust localization would allow the development of several new indoor location based services. Localization of mobile nodes is a key requirement in navigating, tracking and various other applications. Indoor positioning systems (IPS) are the systems where location of a mobile node is estimated based on different attributes inferred from stationary nodes. The applications of an accurate IPS encompass a wide range of applications. For instance, huge shopping malls, airport, supermarkets, museums, storage facilities and parking plazas are few

M. Weichold et al. (Eds.): CROWNCOM 2015, LNICST 156, pp. 499–510, 2015.
DOI: 10.1007/978-3-319-24540-9_41

examples where IPS can revolutionize the domain of location based services. In addition, robotic mail delivery, context aware robotics, smart rooms and interactive humanoid robots etc. are also amongst possible applications out of the myriads of possibilities, yet to be explored.

Indoor localization and tracking systems may be broadly classified into two types; infrastructure free (IF) localization and infrastructure based (IB) localization [1]. In IF localization, no new infrastructure is required for localization of mobile nodes. Such schemes assume universal WiFi availability (indoors) and thus localization can be implemented on smart phones with no requirement of additional infrastructure. IB localization techniques require additional hardware (other than a smart phone) and careful planning (e.g. deployment of sensors, beacons, routers, antennas, development of maps, etc.) to carry out localization. Although IF localization is gaining genuine interest from research and industrial community, there are areas where IB localization is preferred over IF localization. For instance, for localization of miners in an underground mine, for robot navigation in warehouses and localization of expensive equipment in hospitals or museums, designing a system based on Wi-Fi and smart phone devices may not be a suitable choice.

Localization schemes (be it IF or IB) in general are classified in many ways; range-free or range-based, distributed or centralized, geometric or non geometric, etc. Range-based methods include exploitation of quantities such as TOA (Time of Arrival), TDOA (Time Difference of Arrival), AOA (Angle of Arrival) or RSS (Received Signal Strength) [2] whereas range free localization rely on attributes like number of hops, node density etc [3]. Range-based approaches give better estimates of localization as compared to range-free methods as they are relatively more accurate with providing the information about the direction of the signal source. They exploit the TOA and TDOA information to find out the AOA. On the other hand, the RSS information provides an estimate about the range/distance of the signal source with careful modeling of the environment.

This paper presents SHARF; a hybrid approach for localizing a source based on TDOA and RSS information for acoustic and RF signals and requiring only *one* beacon node and *one* anchor node. Hybrid localization has been previously investigated but most of the previous work is generally concentrated on the hybrid algorithms[4] to find a sweet spot of trade-off between computational complexity and localization accuracy. Some systems exploit the special sensor array structures [5] for better localization accuracy. Unlike these approaches, the proposed system combines the strengths of the two methods of localization to provide a new insight into the localization and accurate position estimation. The TDOA based acoustic localization approach is very accurate if the sensor and beacon nodes satisfy Fraunhofer plane wave condition. However, when it comes to ranging a source in the far field, the acoustic localization system presents problems with a single node since the distance of sensor and beacon node does not remain comparable to the distance between microphone sensors in the array and hence, erroneous estimates appear. To overcome this problem, at least three nodes are required for location estimation through trilateration; which presents its own challenges like clock synchronization and time stamping of events etc. Although acoustic localization has been attempted with 2 sensor nodes with reflective surface [6], the cost of complexity is high. Similarly, the RF localization based on RSS does not determine the direction of arrival with a single node and hence three nodes are required for trilateration in this case too [7]. Moreover, finding the AOA with wireless signals by exploiting TDOA requires at least two antennas and very high speed and high resolution Analog to Digital Converter (ADC) units which are very expensive. The scheme presented in this paper brings down the number of sensor nodes to just one; a single RF-acoustic sensor node for localization and ranging. To the best of authors' knowledge, location estimation with such precision and accuracy has never been achieved with a single node before. Thus SHARF is first of its kind. The scheme presented in [8] is, however, somehow akin to it. Furthermore, in order to cater for the outliers of RF based ranging, we employ a moving average filter and a clustering algorithm which rejects the anomalies in the RSS values. This takes care of rapid fluctuations due to received multi-paths.

The rest of the paper is organized as follows. Section 2 presents the system model and the proposed approach for hybrid localization. The hardware implementation is given in section 3. Section 4 presents the experimental results of the proposed localization algorithm based on implementation on actual hardware platform. Finally, section 5 concludes this paper and highlights some future work.

2 System Model and Proposed Approach

The proposed hybrid wireless-acoustic localization system consists of a single wireless-acoustic anchor node and a wireless-acoustic source beacon as the mobile node. The reduction in the number of anchor nodes from (at least) 3 to 1 shows a three-folds decrease in the cost of the entire setup. In this paper, we assume that we are localizing a single target node. However, extension can be done for multiple targets.

Following are the key features of our measurement setup:

1. The deployed anchor node has complete information about its location and orientation in the environment.
2. The beacon node is present in the far field and behaves as a point source.
3. The nature of acoustic signals from the source are discontinuous and impulsive.
4. Localization is being done in 2D i.e. elevation information is not incorporated in the system. Moreover, the localization is carried out in the coverage area of the anchor node.
5. It is assumed that the link between anchor node and the target node follows the following path loss model

$$P_r = P_r(d_0) + K + 10\gamma log_{10}(d_0/d) + \zeta \tag{1}$$

where P_r represents the received power, $P_r(d_0)$ is the received signal strength at reference distance d_0 which is usually taken to be equal to $1m$, K (in dB)

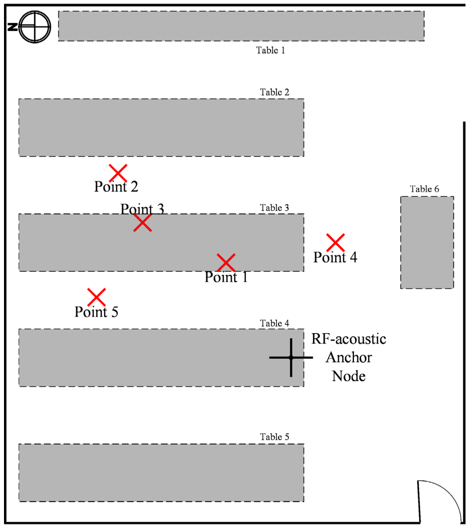

Fig. 1. Experimental setup for wireless-acoustic hybrid localization system. The cross points (X) are the target positions and the origin has been drawn where wireless-acoustic anchor node was placed.

is a unit-less constant depending on channel and antenna characteristics and ζ is a random variable which causes fluctuations in RSS values due to shadowing and changing multipaths. The distribution of ζ is unknown in case of non-stationary indoor environments. $P_r(d_0)$ can be calculated using *Friis* equation or acquired through empirical measurements [9].

6. The RSS values of the beacon signals are averaged over multiple wavelengths through a Moving Average (MA) filter. This averages out the fluctuations due to multi path components and averages out the zero mean noise as well. The MA filter's window size of $M = 15$ is used in our experiments which means that if the target is moving with a speed of 0.3 m/s, with $M = 15$ we roughly average out the RSS values over more than 7 wavelengths of the carrier signal of frequency 433MHz.

Our proposed approach goes through the three stages detailed below before combining the data to reach a final source estimate.

2.1 Path Loss Calculation

Path loss exponent (PLE) is computed through a training phase. Fig. 1 shows the environment of the lab in which the experiments have been conducted. To compute the PLE, RSSI values were recorded at different distances where the anchor node was placed at the coordinates of (0,0). Table 1 shows RSSI values recorded in dBm for multiple distances between the anchor and mobile nodes.

The PLE is computed such that it minimizes the mean squared error between the model and received power during the training phase [10]. Let d_i be the

Table 1. Received Signal Strength Information vs Distance values.

RSSI (dBm)	Distance (m)
-27	1.0
-36	3.17
-43	3.24
-44	3.33
-46	3.9
-49	5.2

distance between the anchor node and the mobile node at the i^{th} iteration, then the received signal power based the model above can be written as:

$$M_{model}(d_i) = K - 10\gamma log_{10}(d_i) \tag{2}$$

where $K \cong 20log_{10}\frac{\lambda}{4\pi d_o}$ is the unit less constant that depends upon the characteristics of the antenna used, d_o is the reference distance in the far field region of the antenna and λ is the wavelength at which the signal is transmitted. In our case the frequency is $433Mhz$ so λ is nearly $0.693m$.

The Mean Square Error (MSE) is than calculated using as under:

$$F(\gamma) = \sum_{i=1}^{n}[M_{measured}(d_i) - M_{model}(d_i)]^2 \tag{3}$$

After taking the first derivative of the above equation and equating that to zero, PLE exponent that minimizes the MSE in the given environment turn out to be 3.26. We make use of this PLE for ranging computations.

2.2 Rejection of Anomalous RSS Values

To reject the anomalous RSS values, we use hyper-ellipsoidal clustering model for outlier detection. Let $R_k = \{r_1, r_2, \cdots r_k\}$ be the first k samples of RSS values collected at the target mobile node in a WSN. Each sample r_i is a $d \times 1$ vector in $\Re^d$, where d is the number of anchor nodes participating in localization. Hyper ellipsoidal outlier detection clusters the normal data points and the points lying outside the clusters are declared as outlier. The boundary of the cluster (an hyper-ellipsoid in this case) is related to a distance metric which typically is a function of mean $m_{R,k}$ and covariance S_k of the incoming RSS data R_k. One example of the distance metric is *Mahalanobis* distance, D_i [11], for which the cluster can be characterized by the following equation

$$e_k(m_R, S_k^{-1}, t) = \{r_i \epsilon \Re^d | \tag{4}$$

$$\underbrace{\sqrt{(r_i - m_{R,k})^T {S_k}^{-1}(r_i - m_{R,k})}}_{D_i = Mahalanobis \quad distance \quad of \quad x_i} \leq t\}$$

where e_k is the set of normal data points whose Mahalanobis distance, $D_i < t$ and t is the *effective* radius of the hyper-ellipsoid. The choice of t depends on the distribution of the normal data points. If the normal data follows a *chi-squared* distribution, it has been shown that up to 98% of the incoming normal data can be enclosed by the boundary of an hyper-ellipsoid, if the effective radius t is chosen such that $t^2 = (\chi_d{}^2)^{-1}_{0.98}$ [11].

2.3 Azimuthal Angle Calculation

The angle of azimuth of the acoustic beacon signal from the target node is found using the conventional TDOA technique. For the simplest case in 2D, the DOA can be computed by finding out the time difference of arrival of the sound signal on two spatially distributed microphones where the distance between them is known, as shown in Fig. 2.

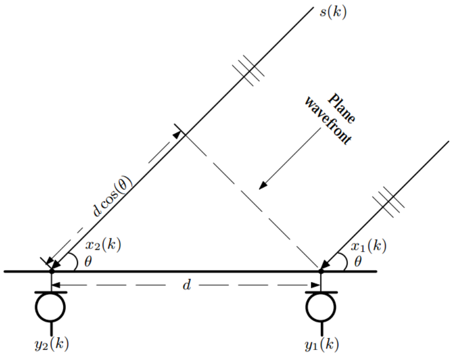

Fig. 2. DOA estimation in 2-D with identical microphones. The source is located in the far field, the incident angle is θ and the spacing between two microphones is d[12].

If microphone $y_1(k)$ is taken as a reference, signal at the second sensor $y_2(k)$ is the delayed version of the same signal at $y_1(k)$, having a delay equal to the time required for the plane wave to travel an extra distance $d\cos\theta$.

Therefore, the TDOA of sound signal between the two sensors is given by:

$$t_d = (d\cos\theta)/c$$

where c is the speed of sound in meters per seconds and t_d is the time delay between two signals .
Also

$$\cos\theta = \frac{c \times t_d}{d} \tag{5}$$

Here $t_d = n_d \times t_s$ where delay index $n_d = n_p - n_{mean}$ is the difference of peak index from mean index and $t_s = 1/f_s$ is the sampling interval if f_s is the sampling frequency.

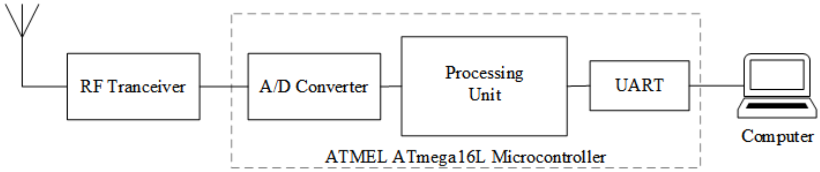

Fig. 3. A block diagram of RF-based localization system.

The value of n_p can be determined by using the cross correlation method [13]. Let the acoustic signal from mics $y_1(k)$ and $y_2(k)$ are digitized and the samples are stored in two arrays $x_1(m)$ and $x_2(m)$ respectively. The correlation between the signals x_1 and x_2 is then given by:

$$R_{x_1 x_2}(n) = \sum_{m=\infty}^{-\infty} x_1(m) x_2(m+n) \tag{6}$$

The peak index n_p will be then:

$$\arg\max_{n} R_{x_1 x_2}(n) \tag{7}$$

If the angle ranges between 0 and 180 and t_d is known, then angle θ can be uniquely determined. Therefore, estimating the incident angle θ is essentially identical to calculating the TDOA of the two signals. By extension of the above, to get the range of 0 to 360, three microphones are used to cater for the ambiguity in the direction of source as we have done in our case. In this way, the entire 2-D planes is covered.

3 Hardware Implementation

3.1 Hardware for RF Measurements

RSS-based localization is tested on low cost, DASH7 compatible, prototype wireless sensor nodes which have been designed and manufactured in-house using off-the-shelf components (COTS). We employed Carrier Sense Multiple Access-Collision Avoidance (CSMA-CA) as our channel access protocol. Atmega 16/32L has been used for processing the data from the wireless sensors. The block diagram of wireless localization system is show in Fig. 3. Table 2 summarizes the specification of RF hardware node.

3.2 Hardware for Acoustics Measurements

The acoustic hardware platform is developed using 32-bit ARM-based M4F-Cortex microcontroller that is capable of working upto 168MHz clock frequency, 3 ADC modules with 12-bits resolution and a maximum sampling rate of 2.4

Table 2. Hardware Summary of RF-node

Components	Used/Implemented
Micro-controller	Atmega 16L/32L (40 Pin, DIP)
Programmer	USBasp
Transceiver	HOPE RFM 69CW
Sensors	Illumination, Temperature
Channel Access	CSMA-CA
Networking Protocol	SNAP
Programming Language	C
Debugging Interface	UART

million samples per second. A built-in floating point unit (FPU) offers more flexibility and computing power to the hardware platform. Such a processing speed and fast ADC is a basic requirement to resolve very small differences in the time of arrival of the acoustic signal on spatially displaced microphones array. The sampling rate we used is $100kHz$ but it can be increased further to improve the resolution of the azimuthal angle. However, to meet the Nyquist criterion of sampling, $44.1kHz$ sampling rate standard as used in audio industry will suffice. The accuracy of the estimated angle of arrival would be lesser though. Condenser type, omni-directional analogue microphones with a sensitivity of $-44 \pm 2dB$ and signal to noise ratio of 60dBA are used with a preamplifier. The preamplifier MAX9814 is a low-cost, high-quality microphone amplifier from Maxim Integrated with built-in Automatic Gain Control (AGC). The reason of using the preamplifier with the microphones is that in order to maintain a particular distance between microphones, they need to be spread apart and the signal is carried through wires. This faint signal if not amplified at the microphone will result in accumulation of noise over the wire. This Variable Gain Amplifier (VGA) provides the ability to pick up weak signals too. An acoustic sensor node consists of three microphones 120° apart in 2-D i.e. at the vertices of a right angled triangle. The measurement setup and the hardware specifications have been presented and listed in the Fig. 4 and Table 3 respectively. The distance between each microphone is 30cm. The source localization or direction estimation is implemented in 2-D and works on the principle of TDOA to find the Direction of Arrival (DOA) of sound from the beacon. The spatial positioning of microphones translates into the signal reaching the microphones at slightly different time intervals. These time delays then indicate the DOA to give the angle of azimuth of the source.

4 Experimental Results

The measurement layout for SHARF with position of the anchor node and test points with mobile node has been shown in Fig. 1. The experiments are conducted in AdCom research lab with an area of 80 m^2. It has six wooden tables

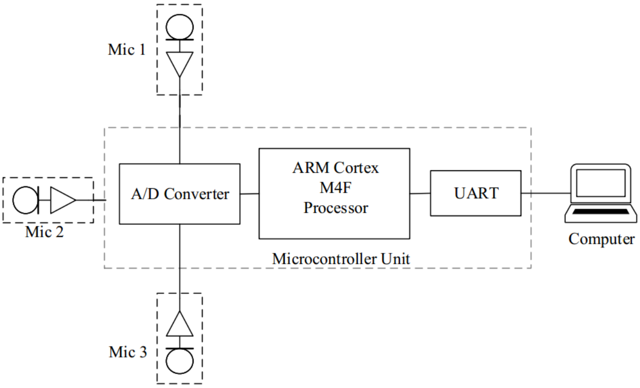

Fig. 4. A block diagram of acoustic localization system.

Table 3. Hardware Summary of acoustic-node

Components	Used/Implemented
Micro-controller	STM32F407VG
Programmer	ST-Link Programmer/Debugger
Microphones sensitivity	$-44 \pm 2dB$
Preamplifier	MAX9814
- Amplifier gain	Variable Gain Adjustment
Programming Language	C
Debugging Interface	ST-Link Debugger

placed in it and two of its walls are of concrete. Additionally there is a plenty of measurement equipment present on the tables to generate multipaths. We assume that the anchor node which had complete information of its position and orientation. It continuously receives the wireless-acoustic beacon signals from the test points marked as X's in the Fig. 1. The RF hardware platform estimates range using RSS values and the acoustic hardware platform provides the azimuthal angle of the target. The results of the localization are then monitored on the PC through a UART interface on the anchor node.

SHARF achieves very good localization accuracy. The mean and standard deviation of location estimation error has been shown in the Fig. 8 over multiple measurements. The results with RF trilateration has also been plotted for alongside to establish the superiority of the proposed scheme.

For the sake of comparison, the error histograms for frequency of error distances for RSS-based trilateration and SHARF at test point 5 for 20 readings have been shown in Fig. 6 and Fig. 7 respectively. The error histograms on this particular point indicate an improvement of around $1.5m$ while using SHARF localization scheme versus only RF-based trilateration scheme.

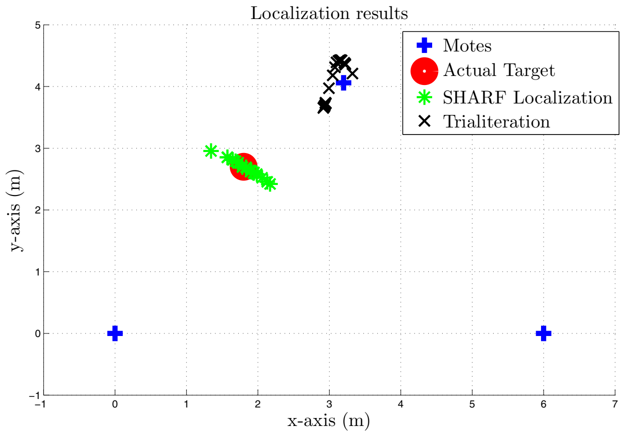

Fig. 5. Ground truth based localization results for SHARF localization and Trilateration systems at point 5.

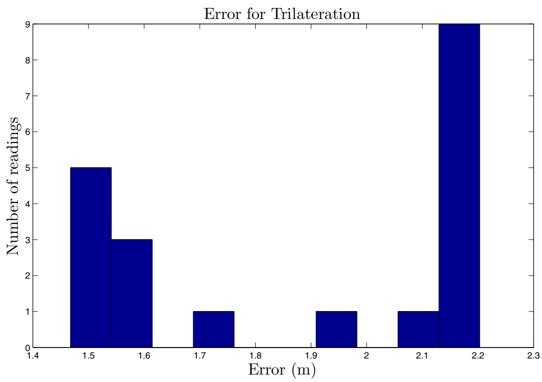

Fig. 6. Distance error histogram for RSS-based Trilateration system at point 5.

Similarly, Fig. 8 shows the anchor node positions, target location and localization results using trilateration and SHARF. We can see for most points, the proposed SHARF scheme outperforms trilateration while using only one beacon node and one anchor node. Please note that for a fair comparison, we use rejection of anomalous RSS values both for trilateration as well as the proposed scheme or otherwise the gain over trilateration can be shown to be much higher. Thus the proposed scheme gives a double advantage; one that it requires only one anchor node and second that it outperforms trilateration-based localization scheme which requires at least three anchor nodes in order to estimate the location of mobile node. Thus SHARF is a localization scheme which not only reduces the size complexity and cost of the system, but also improves the localization accuracy.

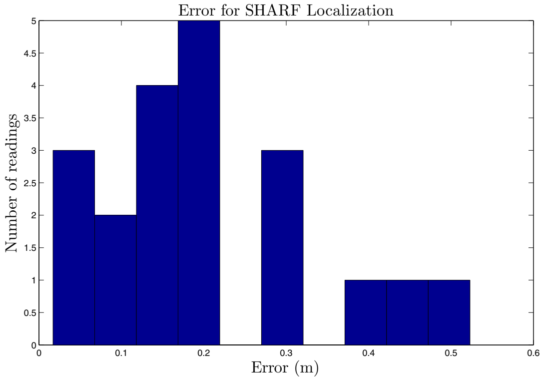

Fig. 7. Distance error histogram for SHARF localization system at point 5.

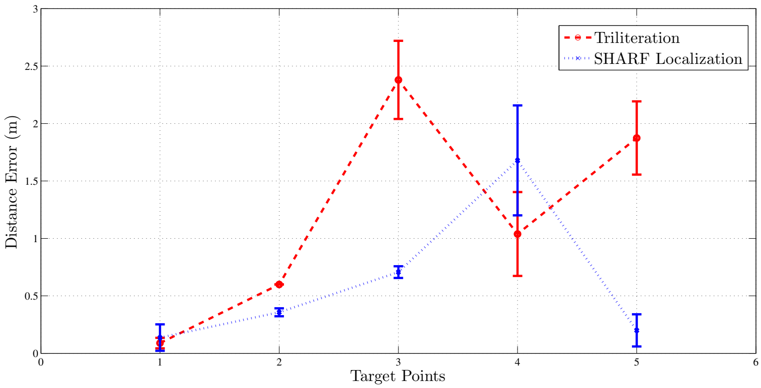

Fig. 8. The mean and standard deviation error bars for SHARF localization and Trilateration systems.

5 Conclusion

This paper proposes and implements SHARF; a single beacon hybrid acoustic-RSS based target localization system. Our solution exploits the strength of TDOA in finding the direction of source from acoustic signals and RSS information in finding the range of the target and combines these information together to mitigate the weakness of acoustic-based localization in ranging and RSS-based localization in direction of the source. RSS-based trilatertion and acoustic-based trilateration systems alone present complexities in synchronization and problem formulation. Moreover, slight error in values of one of the three nodes taking part in trilateration results in a substantial error in the localization error. Cost of the system also goes up by using 3 anchor nodes (at least) for trilateration which, on the other hand, gets reduced to one in case of SHARF. In addition to requiring only a single anchor node for localization, considerable improvement (94%) in mean position error has been achieved using this scheme as compared to the traditional trilateration approach.

References

1. Schneider, D.: New indoor navigation technologies work where gps can't. IEEE Spectrum (2013)
2. Gu, Y., Lo, A., Niemegeers, I.: A survey of indoor positioning systems for wireless personal networks. Communications Surveys & Tutorials, IEEE **11**(1), 13–32 (2009)
3. He, T., Huang, C., Blum, B.M., Stankovic, J.A., Abdelzaher, T.: Range-free localization schemes for large scale sensor networks. In: Proceedings of the 9th Annual International Conference on Mobile Computing and Networking, pp. 81–95. ACM (2003)
4. Peterson, J.M., Kyriakakis, C.: Hybrid algorithm for robust, real-time source localization in reverberant environments. In: Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing, ICASSP 2005, vol. 4, pp. iv-1053. IEEE (2005)
5. DiBiase, J.H.: A high-accuracy, low-latency technique for talker localization in reverberant environments using microphone arrays, Ph.D. dissertation, Brown University (2000)
6. Kietlinski-Zaleski, J., Yamazato, T., Katayama, M.: Experimental validation of TOA UWB positioning with two receivers using known indoor features. In: 2010 IEEE/ION Position Location and Navigation Symposium (PLANS), pp. 505–509. IEEE (2010)
7. So, H.C., Lin, L.: Linear least squares approach for accurate received signal strength based source localization. IEEE Transactions on Signal Processing **59**(8), 4035–4040 (2011)
8. Geng, X., Wang, Y., Feng, H., Chen, Z.: Hybrid radio-map for noise tolerant wireless indoor localization. In: 2014 IEEE 11th International Conference on Networking, Sensing and Control (ICNSC), pp. 233–238. IEEE (2014)
9. Mao, G., Anderson, B., Fidan, B.: Path loss exponent estimation for wireless sensor network localization. Computer Networks **51**(10), 2467–2483 (2007)
10. Goldsmith, A.: Wireless communications. Cambridge University Press (2005)
11. Moshtaghi, M., et. al.: Incremental elliptical boundary estimation for anomaly detection in wireless sensor networks. In: IEEE International Conference on Data Mining (ICDM), pp. 467–476. IEEE (2011)
12. Benesty, J., Chen, J., Huang, Y.: Microphone array signal processing, vol. 1. Springer (2008)
13. Knapp, C., Carter, G.C.: The generalized correlation method for estimation of time delay. IEEE Transactions on Acoustics, Speech and Signal Processing **24**(4), 320–327 (1976)