Enhanced Least Square Method for Indoor Positioning System Using UWB Technology

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Abstract

One of the main radio technologies that could be used for indoor localization is Ultra-wideband, (UWB). It is a short-range RF technology for wireless communication that can be leveraged to detect the location of people, devices, and assets with significant precision. But, it has a major limitation which is the need for a non-line-of-sight (NLOS) identification and mitigation approach to precise location a target in a hard indoor environment. The NLOS approach will complicate the positioning approach. The goals of this work are; i- for saving cost and time of installation of anchor nodes, the minimum required number of anchor nodes have been installed, ii- the accuracy of the created system should be compatible with most various indoor environments. In this work, we create a novel algorithm of Indoor positioning system named Enhanced Linearized Least Square (ELLS) using UWB technology without using an NLOS identification approach. We evaluate and validate the created system by implementing real experiments. The created system has an average positioning accuracy reaching about 0.45 $m^2$of mean square error in a hard environment. It outperforms most indoor positioning systems in the market with less complexity, cost, and more accuracy.

Keywords

Wireless Sensor Network, Indoor Positioning System, UWB, Localization.

Introduction

Continuously, Indoor Positioning Systems (IPS) use a variety of positioning algorithms that vary widely in accuracy, cost, precision, technology, availability, scalability and robustness (Huang H, 2009; Gu Y, 2009). Because of the high need for precise indoor positioning systems, this has become a hotly debated research topic (Jekabsons G, 2011). Position determination is addressed in many techniques by using readily accessible technology. Indoor placement is distinct from outside positioning in that it has its own set of requirements. Five of the most critical quality factors for indoor positioning systems include accuracy and precision of the system, coverage and resolution, the latency in giving location updates, the effect on the building infrastructure, and the impact of random errors on the system (Wu H, 2009).The use of indoor positioning can be found in a variety of settings, including providing indoor navigation systems for the blind, determining the location of devices moving through buildings, assisting museum visitors, locating an emergency exit in a smoke-filled environment, and tracking expensive equipment. IPSs should be carefully selected to meet the needs of various indoor positioning applications, which may need a variety of quality parameters. (1) What are the most convenient technologies for employing the needed IPS? (2) How can the desired IPS be implemented? secondly, To develop an attractive IPS, how can we find the most appealing trade-off between several quality measures? The provision of indoor location-based services is one of the most significant applications of indoor ubiquitous computing. Indoor positioning methods have a daunting challenge: obtaining precise measurements of their current location (Abdulrahman Alarifi, 2016). Acquiring an IP technique that is precise enough, resilient to changes in external circumstances, suited for large regions, and as simple as feasible is a difficult job in indoor positioning systems. A wide range of methods, including fingerprinting algorithms and geometric approaches like trilateration and triangulation, have been proposed. Several IPs are now available for indoor location-based services based on these technologies. No commercialized IP can solve the challenge of locating emergency responders since all solutions involve measurements, calibration, setup, and deployment before deployment (Abbas Albaidhani, 2019). WSN is a current research topic in which sensor modules, wireless communication modules, and information processing modules all connect wirelessly (Aguilar Leocundo, 2011). There is a surprising significance of WSN localization technology in tracking control, emergency rescue, and product labeling. According to Received Signal Strength Indicator (RSSI) ranging, there are various benefits to this technology: The sensor node alone can transmit and receive data packets with RSSI sampling values, and no further hardware is needed (Priwgharm R, 2011). The distance-based positioning technique is straightforward, and the associated software and hardware requirements are modest. Even though wireless signals may be affected by non-line of sight (NLOS) propagation, there is a substantial inaccuracy in RSSI distance calculation, thus it is vital to rectify and increase the predicted distance.

Range-based and range-free strategies are used to locate objects in a radio frequency (RF) communication network (T He, 2003). A radio signal strength indicator is used in the range-free approach (RSSI). From an experimental or theoretical model of signal transmission, it is feasible to get distance and location estimations (P Lourenco, 2013; L Wu, 2009). Using Time of Arrival (TOA), Time Difference of Arrival (TDOA), or Two Way Ranging / Time of Flight (TWR/TOF), it is possible to determine the distance between transceivers based on their arrival times (Z Farid, 2013). In the field of indoor positioning, UWB is a vital technology, and a comparison of current UWB indoor positioning systems is critical. UWB civilian implementations have also been extensively investigated and researched across the globe because of the FCC's recent opposition to the use of unlawful UWB communications. Research and development work on UWB technology has been spurred by the development of international wireless communication standards that advocated the use of UWB technology (Al Ammar, 2014). In terms of RF technology, UWB is regarded as one of the most precise since it is capable of creating centimeter-level positional estimations (M Ridolfi, 2018; S Monica, 2014). It is used extensively for distance estimates and the creation of an indoor positioning system. The propagation channels in the interior environment are referred to as LOS and NLOS. Depending on the radio signal attenuation, the NLOS may be described as soft NLOS or hard NLOS. Due to the exact calculation of signal delays in the UWB signals, it is possible to achieve very high levels of location precision. It is not always possible to determine the distance between the transmitter and receiver based just on propagation distance in an indoor scenario (A Yassin, 2016). Because of this constraint, they are only able to work in low-light conditions. Accuracy in the LOS channel is excellent, but in the NLOS channel, the error in the calculated distance is large, which has a negative impact on positioning accuracy (Abbas Albaidhani, 2020; Y Wang, 2012). An NLOS identification technique is critical when employing UWB technology to establish an IP system in an interior setting, particularly if the environment is hostile. A new NLOS identifying mechanism will complicate the Internet Protocol (IP) system, making it more difficult, complicated, and expensive to deploy.

The objectives of this work are as follows: i- to minimize the cost and time associated with anchor node installation, the bare minimum number of anchor nodes is placed; ii- the accuracy of the constructed system should be compatible with a wide variety of interior situations.

To accomplish the above objective, we propose the following contribution: I By avoiding the use of any NLOS identification method, ii) the created system avoids mathematical complexity, iii) the required number of anchor nodes is kept to a minimum (4) anchor nodes are installed in a harsh environment, and iv) in a narrow area, the anchor nodes are installed randomly with a small number of them, thereby avoiding the cost and time associated with geometric installation.

The following sections comprise the paper: Section 2 contains a review of relevant works, whereas Section 3 has the system prototype. Section 4 discusses experimental assessment and validation. Section 5 contains the conclusion and discussion. Finally, section 6 includes a conclusion and suggestions for further study.

Related Work Survey

The authors of (Abbas Albaidhani, 2020) created an indoor positioning approach named modified linearized least-square position approach. The goal of this work is to obtain a precise estimated positioning approach. They use the combination approach to arrange the anchor nodes into distinct groups. Then, they implemented the weighted least square method by each anchor node group to allow each group to compute the target position. The authors used the anchor selection method (Abbas Albaidhani, 2016) to select the appropriate group that has the best estimation position. The Weighted Geometric Dilution of Precision (WGDOP) approach is used to choose the optimal anchor group for NLOS detection and mitigation. When moving the mobile station, a Linear Least Squares (LLS) method is updated to use just the variance of measured distances online to determine the new location. The improved LLS is briefly described in the section on system prototypes (following section). The algorithm was created in two basic steps. The first step involves randomly placing *n* anchor nodes in a harsh environment and clustering them into groups of four to *n-1* nodes that communicate with the mobile station through UWB technology. To find the mobile station, each group uses a standard Linear Least Squares (LLS) approach. The best-performing anchor node group is then picked online using criteria called Weighted Geometric Dilution of Precision (WGDOP). To reduce consumption time and system complexity, we avoid employing any NLOS approaches. In the second phase, we use the improved LLS (created by adding an online vector of measurement distance variance to the measurement distance vector in the prime equation of the original LLS) to reposition the mobile device relative to the chosen group. The achieved positioning precision is around $25cm^2$ MSE, which is significantly better than previous IP systems published in the recent decade.

The author covers anchor-based 3D localisation based on range measurements in his 2010 publication. Following the establishment of the Cramer Rao Bound (CRB) and its relationship to GDOP, three numerical optimization methods, such as Newton-Raphson (NR), Gauss-Newton (GN), and Steepest Descent (SD), are presented for ML and LS localization algorithms and iterative approaches to the ML/LS estimation (SD). In our numerical models, the geometric relationship between the agent and anchors, as well as the distinction between the CRB and GDOP, can be clearly seen. Our results show that the best ML/LS estimator is ML, but the LS estimate isn't. NR, GN and SD approaches may be used to approach ML/LS estimation. The number of anchors is also shown to affect the CRB. According to equation1 of the ML technique, the distance measurement is maximized in order to get the agent's location.

$$arg\ min_p \left(\sum_{k=1}^{k} \frac{(r_k - d_k)^2}{\sigma_k^2} \right) \qquad (1)$$

Where *r* and *d* are the real and estimated distances, respectively, and r is assumed to be a zero-mean independent Gaussian process with variances of σ^2, and k is the total number of anchor nodes (LEDs). The distance between a starting point and the anchor nodes is represented by *r_ k*. The initial point in traditional ML is fixed and chosen at random. Using simulated examples, We demonstrate how the geometry of the link between the agent and anchors may affect localization performance, particularly outside the cube encompassed by anchors and in the direction from the cube center to each anchor. When the changes in range error variations under different SNRs are not modest, the GDOP is not a good metric of localization performance. For example, we demonstrate that the SD technique may be used to approximate ML/LS estimation, although it has a slow convergence rate. It is clear that the ML estimator is the best since it can attain the CRB in high SNR circumstances, but the LS estimator can only provide mediocre localization accuracy. While the number of anchors that may be used to get range information is reduced, the performance of the agent is degraded.

Alwin Poulose, who died in 2018, will be remembered in 2019 (Poulose, 2019). In this article, several UWB system localization approaches were examined in detail. There are two metrics used to measure algorithm performance: the root means square and the cumulative distribution function. The results of the trial suggest that a variety of UWB indoor positioning approaches are successful. Compared to other methods like linearized least squares and weighted centroids, this one is more efficient. The linearized least square approach was shown to be unsuccessful for indoor UWB localization, as evidenced by the testing.

To locate a UWB within a building, fingerprint estimates are the most common method of locating it. When comparing the current tag distance to an existing fingerprint database, this method builds a fingerprint map based on the relationship between tags and anchors. There are many grid points across the trial area where we measure the distance from each of these places to a tag. The offline phase is the name given to this stage. Repeat the experiment and note the tag distance from each anchor after establishing the fingerprint database. Online phase is the term for this stage. The Euclidian distance is calculated by comparing the distance data from the online and offline phases. The shortest possible Euclidian distance is used to determine the tag's actual location.

Table 1 Performance of the localization algorithms for LOS condition

Localization method	Mean error (m)	Max. error (m)	Min. error (m)	Average computation time (m)
LLSE	0.7491	1.0101	0.0017	1.5136
FPE	0.7273	0.83	0.0053	1.4649
WCE	0.7009	0.96	0.001	1.4578

FPE beats the LLSE and WCE algorithms in terms of location accuracy, according to Table 1. However, FPE requires prior knowledge of the experiment region as well as manpower to collect fingerprint data. FPE must update the fingerprint database whenever the experiment setting changes.

The performance of various indoor localization techniques for UWB was investigated in this paper. For both LOS and NLOS circumstances, the FPE algorithm performs better. FPE, on the other hand, has a longer computing time and is more complex than LLSE and WCE. The precision of the position is determined by the length of the experiment. The FPE algorithm performs worse as the experiment time increases as compared to LLSE. With more time, the LLSE algorithm can accurately position itself. In comparison to the LLSE, the performance of the FPE and WCE is comparable at times.

It was revealed that RSSI range error has a direct influence on the system's overall positioning accuracy, and so a weighted maximum likelihood estimation positioning technique was presented in 2017 by (Qiang, 2017). A weight matrix of the distance's inverse square is added into the standard maximum likelihood estimation algorithm as a theoretical derivation shows that the square of distance and method placement accuracy are inversely related. This technique decreases errors by 0.45-1.87 m and increases accuracy with the same error range when tested, according to findings. Based on "the greater the distance between nodes, the corresponding coordinates of nodes, the lower [the weight]," we'll come up with an entirely new method for computing an appropriate weighting matrix. When a mobile node is in close proximity to a fixed anchor node, that distance is measured. Mathematical software for the experimental simulation development is 2013 MATLAB, which has an experimental site that is around 50 meters by 50 meters. Divided into six 6-by-6-by-6 squares with 198 corners, the entire area is divided into six 6-by-6-by-6 squares. In each experiment, just one of the vertices represents the actual location of the mobile nodes. The following simulation was run to evaluate the aforesaid weight positioning algorithm and increase positioning accuracy: The anchor node positions are created at random, and the true position of the movable node is determined by randomly selecting a vertex. The distance between the mobile and anchor nodes is multiplied by a random white noise with a mean of 0 and a variation of 2 to replicate the real-world environment. Our weight matrix W will be the 1/d2 matrix since it's easier to understand. The 1/d2 matrix is the term given to the localization process since it estimates location more closely than other weights do. The weight of 1, 1/d, and 1/d2 placement strategies are used for the 100 simulations to provide three different results. Localization algorithms under different weighting matrices have a minimum error of 0.55 m, a maximum error of 10.05 m, and an average error of 3.68 to 4.22 m, respectively. Weights 1/d2 are 0.48-0.58m more accurate in their location than other types of weights. Antenna node density more than 10%, and the 1/d2 weight of a maximum likelihood estimate of positioning error, is smaller than that of the other, and 1/d2 weight is less than the other. 3D weighted maximum likelihood estimation is more accurate than the 3D maximum likelihood estimation method and has a lower error rate than the previous approach. Based on the RSSI approach, as a consequence, it is worthwhile to investigate the problem to assure adequate weight and RSSI-ranging accuracy.

In 2021 Wenxu Wang, Particle filtering is a prominent method for tackling the indoor dynamic localization problem based on Wi-Fi measurements. However, one disadvantage of this approach is that accurate findings in real surroundings require a huge number of particles. The reason for this disadvantage is that traditional particle filtration wastes many superfluous particles in this application (Wenxu Wang, 2021). To address this, we present the maximum likelihood particle filter, a revolutionary particle filtering approach (MLPF). The key concept is to combine the particle prediction and update phases into a single step that makes efficient use of all particles. This dramatically decreases the number of particles, resulting in numerically practical, high-accuracy algorithms. We present experimental results based on genuine data to back up our argument.

Maximum probability particle filtering is a novel indoor positioning approach that we suggested. Combining prediction and update procedures of a standard particle filter into one step needs the solution of a maximum likelihood estimation issue as its basic idea. As a result, particles are better used. In comparison to particle filtering, the method obtained delivers high precision indoor placement with a significantly smaller number of particles. This makes real-time applications numerically possible. We used real data to back up our assertions in a Wi-Fi indoor positioning experiment. Our experiments show that using our strategy leads to significant accuracy gains, with sub-meter indoor localization accuracy.

System Prototype

In this section, we present the entire structure of the proposed IP system. In this work, we install four anchor nodes randomly (at least we need four nodes to compute target position in space) as shown in figure 1. UWB technology by an electronic transceiver named decawave (tow way ranging) (TREK 1000) evaluation kit is used in this experiment to communicate with a moving target inside a hard indoor environment. All specifications and characteristics of this sensor is explained briefly by (Decawave, 2014). Also, the transceivers have to be placed in the Fresnel zone (FZ) (A Albaidhani, 2016). In equation 2 below, R expresses the radius of the first Fresnel zone, λ denotes the wavelength of the radio signal, and the distance between sites is denoted by r.

$$R = \frac{1}{2}\sqrt{\lambda . r} \qquad (2)$$

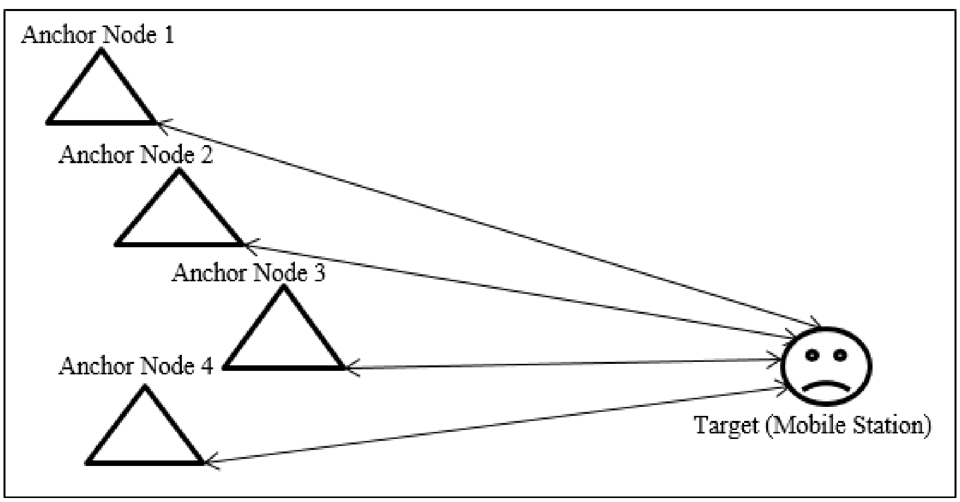


Figure 1 Mobile station positioning in three space

After anchor nodes and target connection, we extract the measured distance between every anchor node and the target as shown in figure above. Then, we compute estimated mobile position using the proposed IP algorithm as explained later. In the subsection below we explain the least square estimation method for localization.

a. Least Square Method

The Euclidian distance between any two points in space (three dimensions) is expressed as in equation 3.

$$r = \sqrt{(x_n - x)^2 + (y_n - y)^2 + (z_n - z)^2} \quad (3)$$

Where, x_n, y_n, z_n denotes the coordinates of the anchor node and n denotes the index of the anchor node. x, y, z denote the coordinates of the mobile station (M).

A positioning algorithm should be applied once the distances (*r*) between entire anchor nodes and the target are measured to compute the mobile position. The common and simplest positioning approach that has been implemented for RSS-based localization is the hyperbolic positioning algorithm. As we explained above, *r* denotes the real distance and let denote the measured distance extracted from the sensor as d then the error is computed as presented in equation 4.

$$\epsilon = \sum_{i=1}^{m} d_i - r_i \quad (4)$$

Where, *m* denotes the index of the mobile station. The estimated position $\widehat{M}$ could be computed as shown in equation 5 iteratively utilizing a straight gradient method for an example.

$$\widehat{M} = \begin{bmatrix} \hat{x} \\ \hat{y} \\ \hat{z} \end{bmatrix}_{m+1} = \begin{bmatrix} \hat{x} \\ \hat{y} \\ \hat{z} \end{bmatrix}_{m} - \alpha \begin{bmatrix} \frac{\varphi\epsilon}{\varphi x} \\ \frac{\varphi\epsilon}{\varphi y} \\ \frac{\varphi\epsilon}{\varphi z} \end{bmatrix}_{x=\widehat{x_m}, y=\widehat{y_m}, z=\widehat{z_m}} \quad (5)$$

Where, α denotes a scalar selected to minimize ϵ. Also, $\hat{x}, \hat{y}, and\ \hat{z}$ denote the estimated coordinates of the $\widehat{M}$. In the aforementioned equation (equation 5), an initial value of the position estimation is needed. To convert this nonlinear into a linear problem, the hyperbolic positioning algorithm is used by implementing least square method as we presented. Equation 6 shows the compact equation of linearized least square method (LLS).

$$\widehat{M} = \begin{bmatrix} \hat{x} \\ \hat{y} \\ \hat{z} \end{bmatrix} = (A^T A)^{-1} A^t b + \begin{bmatrix} x_1 \\ y_1 \\ z_1 \end{bmatrix} \quad (6)$$

Where, A denotes the matrix of the anchor nodes coordinates, and b denotes the estimated distances measurements as shown below.

$$A = \begin{bmatrix} x_2 - x_1 & y_2 - y_1 & z_2 - z_1 \\ x_3 - x_1 & y_3 - y_1 & z_3 - z_1 \\ \vdots & \vdots & \\ x_n - x_1 & y_n - y_1 & z_n - z_1 \end{bmatrix}$$

$$b = 0.5 \begin{bmatrix} (x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2 + d_1^2 - d_2^2 \\ (x_3 - y_1)^2 + (y_3 - y_1)^2 + (z_3 - z_1)^2 + d_1^2 - d_3^2 \vdots \\ (x_n - x_1)^2 + (y_n - y_1)^2 + (z_n - z_1)^2 + d_1^2 - d_n^2 \end{bmatrix}$$

The proposed system (ELLS) is explained in the following subsection.

b. Proposed System

The original modified linearized least square algorithm (MLLS) derived is used in this work to compute the initial estimated position of $\widehat{M}$. Equation 7 expresses the original MLLS.

$$\widehat{M} = \begin{bmatrix} \hat{x} \\ \hat{y} \\ \hat{z} \end{bmatrix} = (A^T A)^{-1} A^T (b - T) + \begin{bmatrix} x_1 \\ y_1 \\ z_1 \end{bmatrix} \quad (7)$$

Where, T denotes the vector of variance of measured distances expressed. The variance of the distance is extracted in live statues from the UWB device when this device provides 8 distance measurements every seconds.

$$T = \alpha \begin{bmatrix} \sigma_1^2 & - & \sigma_2^2 \\ \sigma_1^2 & - & \sigma_3^2 \\ & \vdots & \\ \sigma_1^2 & - & \sigma_n^2 \end{bmatrix}$$

where α denotes a scalar which is determined based on the type of environment and σ denotes the variance of the measured distance by the sensor.

Then, after having it, we compute the new estimated distance $(\hat{d})$ between the initial estimated position $(\widehat{M})$ and each anchor node as shown in equation 8.

$$\hat{d} = \left\| An - \widehat{M} \right\| = \sqrt{(x_n - \hat{x})^2 + (y_n - \hat{y})^2 + (z_n - \hat{z})^2} \quad (8)$$

Finally, we modify b vector by the new estimated distance to be $(\hat{b})$ using the new distances $\hat{d}$ as shown below, and maiming the value of the scaler (α) that multiplies the T vector in the original MLLS to recomputed the mobile position using the proposed modified least square method by as shown in equation 9 below.

$$\hat{b} = 0.5 \begin{bmatrix} (x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2 + \widehat{d_1}^2 - \widehat{d_2}^2 \\ (x_3 - y_1)^2 + (y_3 - y_1)^2 + (z_3 - z_1)^2 + \widehat{d_1}^2 - \widehat{d_3}^2 \vdots \\ (x_n - x_1)^2 + (y_n - y_1)^2 + (z_n - z_1)^2 + \widehat{d_1}^2 - \widehat{d_n}^2 \end{bmatrix}$$

$$\widehat{M} = \begin{bmatrix} \hat{x} \\ \hat{y} \\ \hat{z} \end{bmatrix} = (A^T A)^{-1} A^T \left(\hat{b} - \hat{T}\right) + \begin{bmatrix} x_1 \\ y_1 \\ z_1 \end{bmatrix} \quad (9)$$

$$\hat{T} = \hat{\alpha} \begin{bmatrix} \sigma_1^2 & - & \sigma_2^2 \\ \sigma_1^2 & - & \sigma_3^2 \\ & \vdots & \\ \sigma_1^2 & - & \sigma_n^2 \end{bmatrix}$$

Where $\hat{\alpha}$, denotes the new scaler which is should be lower than the original α and based on the indoor environment. This scaler (α) should be lower than the scaler with the original scaler. Also, it is based on the indoor environment as shown in the diagram below.

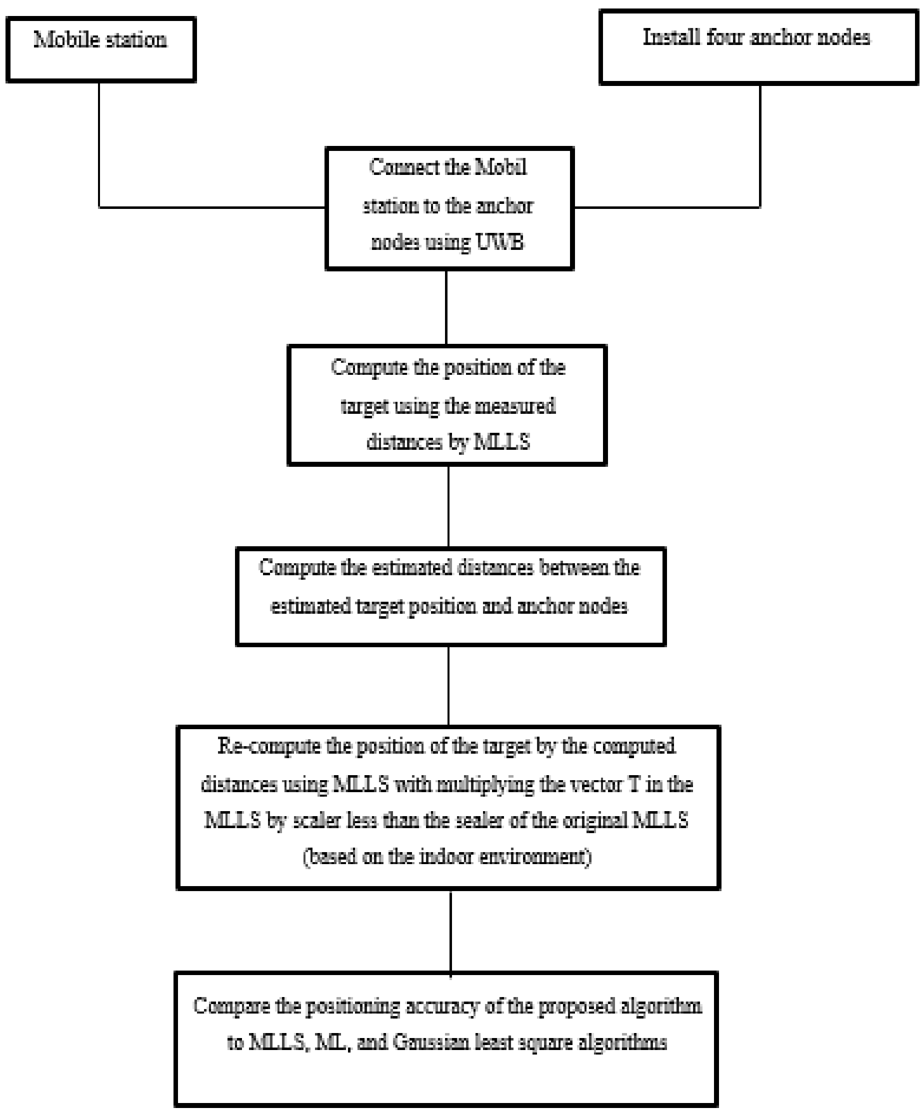


Figure 1.1 Diagram of the proposed IPs approach

Experimental Evaluation and Validation

In this work, we present real experiment to evaluate the proposed algorithm of IP system (ELLS) using UWB technology. The UWB sensor used for this experiment is called Decawave 1000 (EVK 1000, TREK 1000). This device manufactured by Decawave company was explained briefly. The following subsection explains the installation of these devices as anchor nodes and a target.

a) Setting up the Experiential Scenarios

This work is presented in the ground and first floor in the Al-Manara College For Medical Sciences. The area used for the experiment is about 4.8 m width, 20 m length, and 4.4 m high. Four anchor nodes are installed randomly with known positions in a narrow area (4 m length and 3 m width) to simulate the implementation of the created IP system for emergency situation. These anchor nodes are placed in 1.8 m above the ground and communicated to a target using UWB technology as shown in figure 2. To maintain signal strength, the UWB sensors are placed in a Fresnel Zone (FZ) as presented in equation 10 below. In the equation below, r is presented for radius of the first Fresnel zone, λ denotes the wavelength of the radio signal, and the distance between sites is denoted by d. Table 2. depicts the FZ of the two channel models used by UWB EVK 1000. We implanted channel model in this experiment. As mentioned by, the channel 2. outperforms channel 3. in indoor environment, so, we implanted channel 2 model in this work.

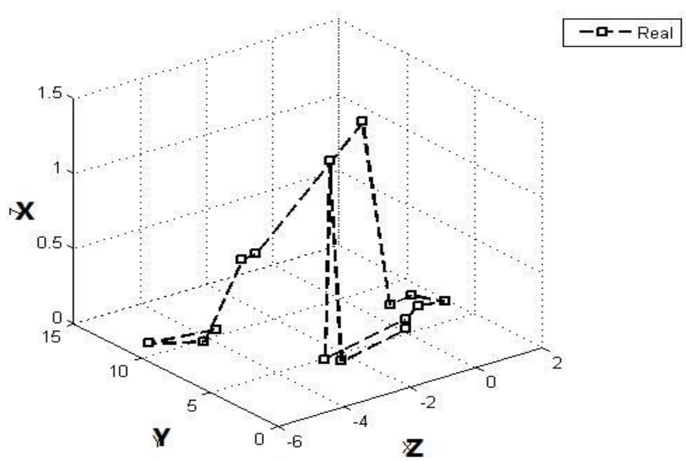
$$r = 0.5\sqrt{\lambda . d} \quad (10)$$

Figure 2 The installed anchor nodes in the real environment

Table 2 Fresnel Zone (FZ) for Channel 2 and Channel 3

Channel	Fc (MHZ)	Band Width (MHZ)	FZ Radius Bottom cm	FZ Radius Top cm
2	3993.6	3774 - 4243.2	44.6	42
3	4992.8	4243.2 - 4742.4	42	39

Two different track scenarios of the target while moving in an indoor harsh environment throw different propagation channels are present as shown in figurer 3 (a and b).



a. Real track of scinario 1

Figure 3 The real track of scenario 1

b) Proposed Approach (ELLS)

As mentioned in figure 2, the proposed approach consists of different steps. In the beginning, we installed four anchor nodes having three coordinates as presented below.

Anchor node 1 (A1): x1=0 m, y1=0 m, z1=0 m. Anchor node 2 (A2): x2=1.84 m, y2=3.67 m, z2=0 m, Anchor nod 3 (A3): x3=3.70 m, y3=1.22 m, z3=0 m. Anchor node 4 (A4): x4=-1.84 m, y4=3.6 m, z4= 0 m.

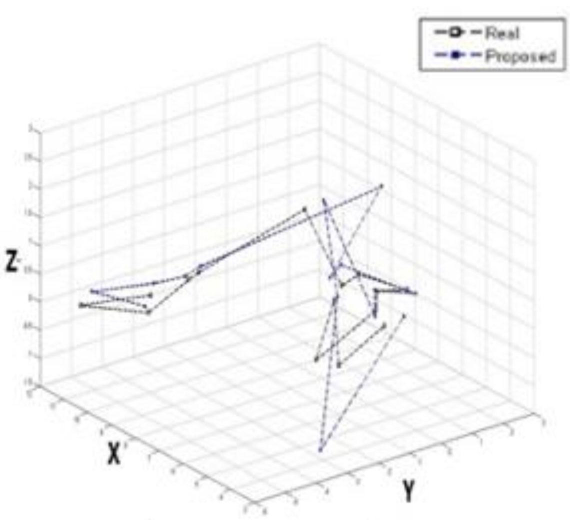
After the communication between all anchor nodes and the target using the UWB devices is commenced, the target starts moving from point to point in the ground floor, then using stairs to go to the first floor creating a track for the first and second scenarios. We compute the estimated position of the target using the modified linearized least square (MLLS) approach. Then, we recomputed the estimated distance using the anchor nodes and the estimated position of the target. So, we modify the vector of the measured distance (b) by replacing the new computed estimated distances ($\hat{b}$) with the measured distances. Also, modifying the scaler that multiplies the vector of the measured distances (T) by multiplying it with the modified scaler ($\hat{\alpha}$). Finally, we compute the new estimated position using equation 8 above.

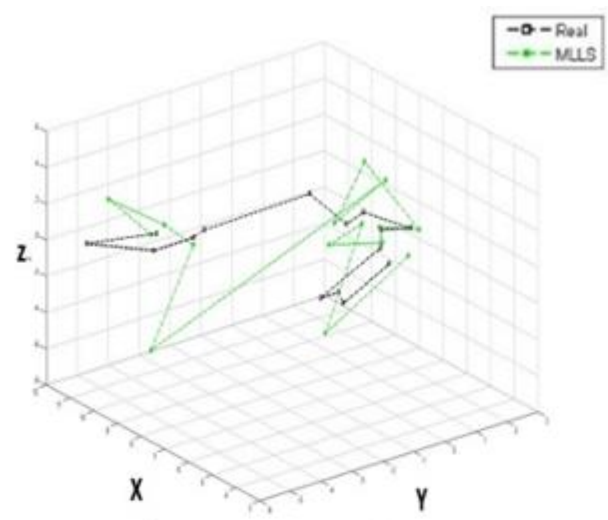
Result and Discussion

As aforementioned in the previous section, two scenarios have been implemented.

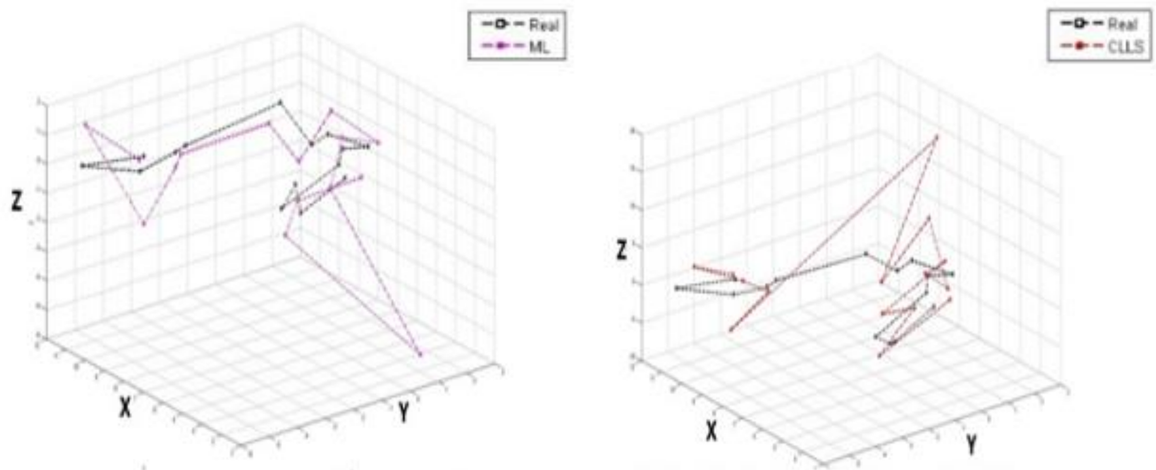
In the first scenario, the target crate a track of 15 points (figure 3) moving around a corridor of 4.8 m width then using the stairs to move up to the second floor. Different type of obstacles (iron, wood, brick, and concrete walls) have been passed by the target, which faces different types of the propagation channels. The propagation channels are line of sight (LOS), soft non line of sight (SNLOS), and hard NLOS (HNLOS) channel.

To evaluate and validate the proposed approach, it is compared to three different approaches, positioning approaches, (conventional linearized least square (CLLS), modified least square (MLLS), and maximum likelihood estimation method (ML)). Figures 4a, 4b, 4c, and 4d present the estimated tracks for the proposed and related approaches The mean square error and its cumulative distrusted function (ECDF) are used to evaluate the proposed approach. As shown in table 3 and figures 4 and 5 respectively, it is so clear that the proposed approach outperforms the other approaches when having about 0.3 m^2 of MSE in average and 0.0140 m^2 of MSE in minimum values, and 2.65 m^2 of MSE in maximum value, while other approaches have lower accuracy as shown in the tables and figure below.





a. The real and estimated track by the proposed b. The real and estimated track by modified LLS [17]



c. The real and estimated track by maximum likelihood approach [18] d. The real and estimated track by conventional LLS

Figure 4 The estimated tracks by proposed, MLLS, CLLS, and ML approaches (scenario 1)

Figure 5 depicts the ECDF of MSE for the proposed and three related positioning approaches. Table 3 presents the average, minimum, and maximal values of the proposed and three related approaches.

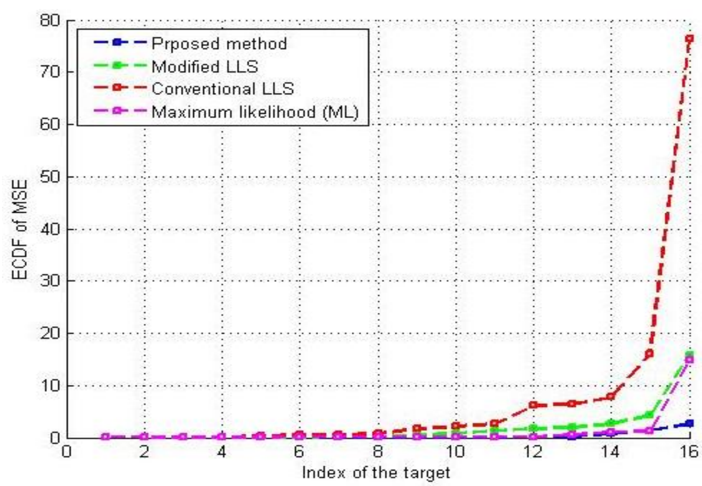


Figure 5 The ECDF of MSE for the proposed and three related approaches of positioning (scenario 1)

Table 3 The MSE values for the proposed and three related approaches of positioning (scenario 1)

MSE m^2	**Proposed approach**	**ML approach**	**MLLS approach**	**CLLS approach**
Average	0.3680	1.2668	1.9767	8.1088
Minimum	0.0104	0.0233	0.0104	0.0104
Maximum	2.6206	14.8478	15.8680	76.3591

In the second scenario, we created different mobile track travelling through different propagation channel. This track consists of 14 different points. Figure 6 presents the real target track. we installed four anchor nodes having three coordinates as presented below.

Anchor node 1 (A1): x1=0 m, y1=0 m, z1=0 m. Anchor node 2 (A2): x2=1.84 m, y2=3.67 m, z2=0 m, Anchor nod 3 (A3): x3=3.70 m, y3=1.22 m, z3=0 m. Anchor node 4 (A4): x4=-1.84 m, y4=3.6 m, z4= 0 m.

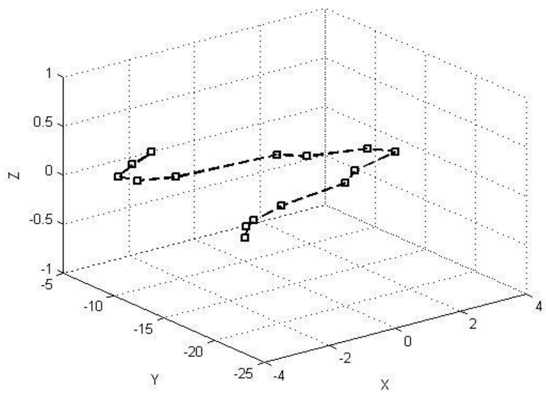
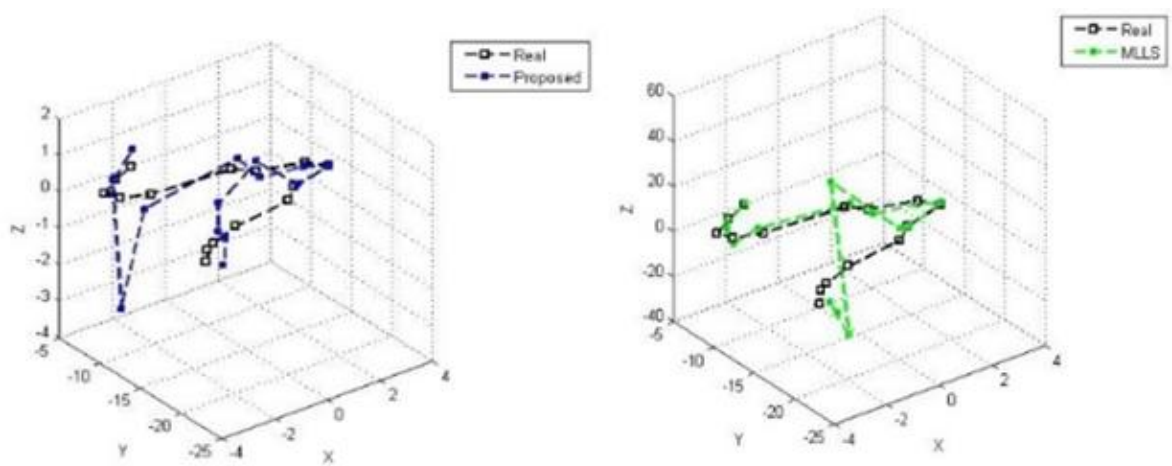
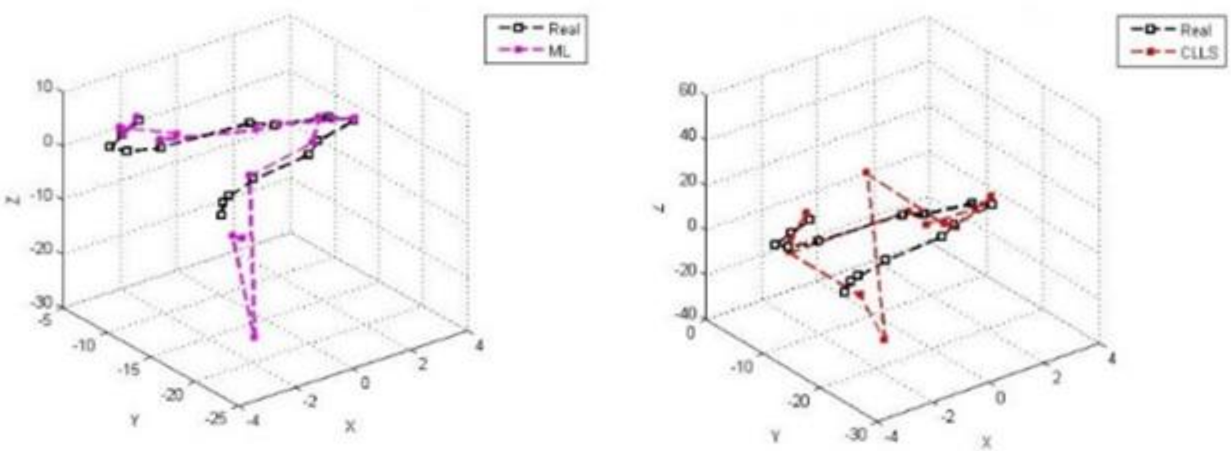


Figure 6 Real track (14 points) in scenario2

Figure 7 presents the real target with the estimated targets by the proposed approach, Modified LLS, conventional LLS, and Maximum likelihood.



a. The real track and the proposed track b. The real track and the estimated track by [17] MLLS



c. The real track and the estimated track by maximum likelihood approach [18] d. The real track and the estimated track by conventional LLS

Figure 7 The proposed algorithm compared to three different IP systems (scenario 2)

To finalize the evaluation process, we also compute the ECDF of MSE for the proposed approach and three different related approaches. Figure 8 presents the ECDF.

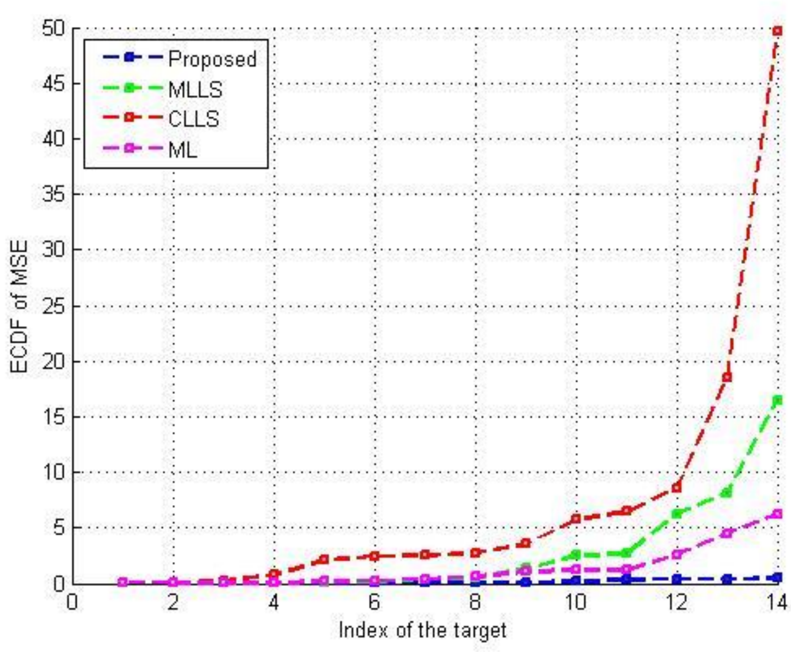


Figure 8 The ECDF of MSE (m^2) of the proposed and three related IP systems (Scenario 2)

Table 3 presents The MSE of the proposed approach and the related IP systems in scenario 2. The results of scenarios 1 and 2 show that the proposed approach significantly outperforms the other related approaches.

Table 3 The MSE values for the proposed and three related approaches of positioning (scenario 2)

MSE m^2	Proposed approach	ML approach	MLLS approach	CLLS approach
Average	0.1716	1.4012	2.9733	7.9604
Minimum	0.0172	0.0086	0.0104	0.0104
Maximum	0.4726	6.2266	0.0173	0.0535

From these figures and tables, we can observe that the related approaches used in this work droop deeply the accuracy in some points of both scenarios. This is because these points face significant distance measurements error reaching about $0.9\ m$ due to the UWB signal travels through a hard NLOS propagation channels. While, the proposed approach fixes this problem to enhance significantly the accuracy for the same situation.

Conclusion

The positioning accuracy with saving cost and the installation time of the anchor nodes in hard environment for different situations such as emergences are the goal of this work. In this paper, we present an IP system named Enhance Linearized Least Square (ELLS) that could be implemented in NLOS and LOS propagation channels using UWB technology. This approach avoids the cost and complexity by using minimum required anchor nodes and avoiding the NLOS identification and mitigation process. The created approach is implemented by real experiments with two different scenarios. Also, it is evaluated and validated by comparing it to different related IP approaches. We confidently claim that the created approach outperforms most IP systems in the market by enhancing the positioning accuracy to reach about $0.45\ m^2$ in average for different environments.

References

Huang, H., & Gartner, G. (2009). A survey of mobile indoor navigation systems. *In Cartography in Central and Eastern Europe*, Springer, 305-319.

Gu, Y., Lo, A., & Niemegeers, I. (2009). A survey of indoor positioning systems for wireless personal networks. *IEEE Communications surveys & tutorials*, *11*(1), 13-32.

Jekabsons, G., Kairish, V., & Zuravlyov, V. (2011). An Analysis of Wi-Fi Based Indoor Positioning Accuracy. *Sci. J. Riga Tech. Univ. Comput. Sci.*, (44), 131–137.

Wu, H., Marshall, A., & Yu, W. (2007). Path planning and following algorithms in an indoor navigation model for visually impaired. *In Second International Conference on Internet Monitoring and Protection (ICIMP 2007)*, 38-38.

Alarifi, A., Al-Salman, A., Alsaleh, M., Alnafessah, A., Al-Hadhrami, S., Al-Ammar, M.A., & Al-Khalifa, H. S. (2016). Ultra wideband indoor positioning technologies: Analysis and recent advances. *Sensors*, *16*(5), 707. https://doi.org/10.3390/s16050707

Albaidhani, A., Morell, A., & Vicario, J.L. (2019). Anchor selection for UWB indoor positioning. *Transactions on Emerging Telecommunications Technologies, 30*(6), e3598. https://doi.org/10.1002/ett.3598

Aguilar, L., Licea, G., & García-Macías, J. A. (2011). An experimental wireless sensor network applied in engineering courses. *Computer Applications in Engineering Education*, *19*(4), 777-786.

Priwgharm, R., & Chemtanomwong, P. (2011). A comparative study on indoor localization based on RSSI measurement in wireless sensor network. *In eighth international joint conference on computer science and software engineering (JCSSE)*, 1-6.

He, T., Huang, C., Blum, B.M., Stankovic, J.A., & Abdelzaher, T. (2003). Range-free localization schemes for large scale sensor networks. *In Proceedings of the 9th annual international conference on Mobile computing and networking*, 81-95.

Lourenço, P., Batista, P., Oliveira, P., Silvestre, C., & Chen, P. (2013). A received signal strength indication-based localization system. *In 21st Mediterranean Conference on Control and Automation,* 1242-1247.

Wu, L., Meng, M.Q.H., Lin, Z., He, W., Chao, P., & Liang, H. (2009). A practical evaluation of radio signal strength for mobile robot localization. *In IEEE International Conference on Robotics and Biomimetics (ROBIO)*, 516-522.

Farid, Z., Nordin, R., & Ismail, M. (2013). Recent advances in wireless indoor localization techniques and system. *Journal of Computer Networks and Communications*, *2013*.

Al-Ammar, M.A., Alhadhrami, S., Al-Salman, A., Alarifi, A., Al-Khalifa, H.S., Alnafessah, A., & Alsaleh, M. (2014). Comparative survey of indoor positioning technologies, techniques, and algorithms. *In International Conference on Cyberworlds*, 245-252.

Ridolfi, M., Vandermeeren, S., Defraye, J., Steendam, H., Gerlo, J., De Clercq, D., & De Poorter, E. (2018). Experimental evaluation of UWB indoor positioning for sport postures. *Sensors*, *18*(1), 168.

Monica, S., & Ferrari, G. (2014). Accurate indoor localization with UWB wireless sensor networks. *In IEEE 23rd International WETICE Conference*, 287-289.

Yassin, A., Nasser, Y., Awad, M., Al-Dubai, A., Liu, R., Yuen, C., & Aboutanios, E. (2016). Recent advances in indoor localization: A survey on theoretical approaches and applications. *IEEE Communications Surveys & Tutorials*, *19*(2), 1327-1346.

Albaidhani, A., & Alsudani, A. (2020). Anchor selection by geometric dilution of precision for an indoor positioning system using ultra-wide band technology. *IET Wireless Sensor Systems*, *11*(1), 22-31. https://doi.org/10.1049/wss2.12006

Wang, Y., & Xiong, W. (2012). Anchor-based three-dimensional localization using range measurements. *In 8th International Conference on Wireless Communications, Networking and Mobile Computing*, 1-5.

Poulose, A., Eyobu, O.S., Kim, M., & Han, D.S. (2019). Localization error analysis of Indoor positioning System based on UWB measurements. *In Eleventh International Conference on Ubiquitous and Future Networks (ICUFN)*, 84-88.

Qiang, R., Wang, W., Wang, H., He, P., & Huang, W. (2017). 3D maximum likelihood estimation positioning algorithm based on RSSI ranging. *In IEEE 2nd Advanced*

Information Technology, Electronic and Automation Control Conference (IAEAC), 1311-1314.

Wang, W., Marelli, D., & Fu, M. (2021). Dynamic Indoor Localization Using Maximum Likelihood Particle Filtering. *Sensors, 21*(4), 1090.

Decawave, L.T.D. (2014). APS 006 Application notes/ Channel effects on communication range and time stamp accuracy in DW 1000 based system. Version 1.02, 12-16.

Albaidhani, A., Morell, A., & Vicario, J.L. (2016). Ranging in UWB using commercial radio modules: Experimental validation and NLOS mitigation. *In International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, 1-7.