Anchor selection for UWB positioning

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***Abstract*—On the positioning accuracy, the geometric distribution of anchor nodes in wireless sensor networks (WSN) has notable impacts. To select the optimum node combination, conventional methods that depend on geometric dilution of precision (GDOP) demand to spend time on calculating every possible combination of nodes. In military urban and emergency response operations, the time is a crucial issue, and a precise positioning system with a clear indoor covering is a highly prerequisite tool to enhance the safety. It should be seamless, low, frugal, power efficacious, low cost and supply less meter-level accuracy. In this paper, the main goal is to reduce the anchors installation time and to obtain a precise localization system. To obtain this goal, a novel algorithm to build an accurate indoor positioning (IP) system is created using a mean square error (MSE) of an estimated position of a mobile station located by different groups of installed anchor nodes online using least square (LS) method then selecting the group having less MSE value (anchor selection "AS" method) to relocate the mobile station using a weighted least square (WLS) method. The results were highly acceptable for indoor localization because the module attained an MSE localization accuracy in a hard non-line of sight (NLOS) environment below 0.5 m^2 also the time of installing the anchor nodes will be reduced. This paper includes the description of the algorithm and the results of the conducted experiments.**

Keywords- WSN, Indoor Positioning Systems, UWB technology.

I. Introduction

In Indoor Positioning Systems (IPs), obtaining a sufficient precisely indoor positioning method, robust with the changes in the environmental conditions, adequate for expanded areas, and simple as possible is a difficult task. Several methods such as fingerprinting technique and geometric approaches (such as trilateration and triangulation) utilizing distinct technologies have been presented. Based on these methods, different IPs are on the market to present indoor location-based services (ILBS) [1]. However, none of these commercial IPs is adequate to overcome the problem of emergency responders location [2], as all solutions require in advance measurements, calibration, configuration, and deployment.

In emergency scenarios, we don't have enough flexibility and time to install all anchor nodes in a proper situation that may help to obtain an appropriate accuracy for locating a mobile station, but command centers require observing their operational forces, and rescuers demand to detect potential victims to perform a proper care. The most common users for these situations are the firefighters, police, military, and civilians.

In this approach, we provide an IP system suitable for different situations including emergency situations. Indoor environments could be distributed as structured or known, semi-structured and unstructured or unknown depending on the control that the IPs possesses over them [3], [4].

Localization in radio frequency (RF) communication network could be divided into range-free and range-based techniques [5]. The most common range-free method is a radio signal strength indication (RSSI). Theoretical or experimental model of the signal propagation in this method is translated into position or distance estimations [6], [7]. The range based methods are according to distances measurements between transceivers utilizing the time of arrival (TOA), time difference of arrival (TDOA) or tow way ranging time of flight (TWR-TOF) [8].

Of the aforementioned forms of RF technology, ultra wide band (UWB) signal is considered one of the most precise approaches because it can provide location estimates with centimeter-level accuracy [9]. It is widely used for ranging estimation and creating an indoor positioning system. In the indoor environment, the propagation channels could be divided into a line of sight (LOS) and non line of sight (NLOS). Also, the NLOS could be divided into soft NLOS and hard NLOS depending on the attenuation of the radio signal. In the UWB signals, it is possible to transmit and detect very short pulses permitting for high accuracy of positioning because of the accurate calculation of signal delays. In an indoor environment, the propagation path length is not always a good indicator of the ranging between a sender and receiver. Thus, these systems are predominately bounded to the LOS conditions [10]. It precisely measures the distance in the LOS channel but suffers in the NLOS channel, and the error in distance measurements is significantly high [11] [12] which impacts the positioning accuracy.

In this paper, we address the UWB indoor positioning in different environments and scenarios such as an emergency scenario using the AS algorithm. The contributions are i) obtaining of the MSE of the IPs when linearized LS is adopted as the trilateration solution; ii) development of an anchor selection (AS) strategy to mitigate the positioning error induced by the least accurate distance measurements and iii) for using the MSE to evaluate the positioning accuracy of the two anchor group, addition of a virtual node to employ the linearized LS in the case where ambiguity is resolved by additional information.

Our approach helps to avoid installing all anchors in a proper

way and just distribute them randomly to reduce the installation time, and the cost of using a high number of sensors and could be used to precisely locate a mobile station with an error ranges from 10 cm to 50 cm in any environments. It is implemented experimentally using the UWB technology.
The positioning system survey related to this work is presented in Section II. In Section III, the system model is presented. MSE computation in linearized LS is presented in section IV. Section V presents AS algorithm. Experimental and evaluation activities are presented in section VI. Section VII presents results and discussion related to the experimental activities. Finally, section VIII offers a conclusion.

II. Survey of indoor positioning systems

In this section, we present some related works to the anchor selection for UWB indoor positioning.
For the recent decades, the problem of range-based localization system has been studied, especially in radar and sonar field where range measurements are normally acquired from the time of flight (TOF) or the time of difference of arrival (TDOA) measurements. Different IPs using UWB technique are created to locate a mobile station in indoor environments under normal or emergency situation such as in [13, 14, 16, 17, 28], and we state some of them below.
In [15], Mathias Pelka presented an iterative approach for anchors configuration of a positioning system. He used an anchor node randomly as the origin of the coordinate system. For the second anchor position, they presumed that the first two anchors are along one axis and the distance between both anchors is measured. An initial guess of the remaining anchor positions is generated according to a uniform distribution. The algorithm iterates for all anchor nodes in the positioning system. Then, the MSE is computed between the measured and Euclidean distance of the anchor nodes. The MSE is compared with a threshold which depends on the standard deviation of the distance estimation. If the MSE passes the MSE threshold, the algorithm dismisses the solution and starts the process again. The positioning problem with a Taylor expansion combined with a Monte Carlo approach is solved to avoid ambiguity flip. They obtained a mean positioning error of 0.62 m.
The authors of [18], presented a GDOP assisted nodes selection (GANS) algorithm for calculating the GDOP value of the current geometric distribution. As the evaluation criteria, sensor nodes contribution to the total GDOP value is adopted. When The contribution value of the node is higher than the threshold, it will be selected. The anchor nodes subset, which shares in the localization, will be real-time determined. By simulation, This approach shows that the GANS algorithm can minimize the energy consumption of the system while the accuracy of the positioning system has no clear loss, and the computational complexity is decreased.
In 2011, Paula Tarrio presented two weighted least squares methods based on the standard hyperbolic, and circular positioning algorithms that consider the accuracy of the different measurements to obtain a better positioning estimation. With a limited overhead in term of computational cost, these methods present suitable positioning results and obtain a greater robustness to an inaccuracy in channel modeling. The average errors of the positioning systems created by the proposed algorithms are 3.69 m and 2.56 m [19].

In 2017, the authors of [33] presented a modified least squares iterated (MLSI) to minimize errors and optimize the relationship of anchor nodes and a mobile station. The MLSI implements the iteration method to reduce the error of the conventional LS method. That means the MLSI can effectively improve position error rate. When using four anchor nodes system, the average error is 0.8 m. Moreover, increase anchor nodes from four to five; the error value is convergence to 0.48 m. The idea of this approach is to modify the vector of distance measurements used in the main equation of the conventional linearized LS method by involving the average distance error. Also, the positioning accuracy might be increased while implementing more number of the installed anchor nods.

III. System model

In this work, some problems of UWB technology in indoor environments aforementioned in the introduction section likely solved. We create an IP system using MSE to online evaluate the accuracy of the positioning system of a mobile station created using different anchor groups ($\hat{n}$ groups) installed in the environment then selecting the anchor group having better positioning accuracy to relocate the mobile station.
The proposed system consists of a number of wireless sensors created using UWB technology. It consists of n anchor nodes installed randomly and one mobile station moving around. Figure 1 depicts the proposed model when n anchor nodes in the network and only $\hat{n} < n$ optimum anchor node are selected to compute the mobile position (see section V for details). To fit with different situations and one of them is the emergency situation, we took into consideration some constraints may exist in such scenarios, such as the anchor nodes were randomly distributed to reduce the installation time. Also, the installation area should be narrow and not very suitable to distribute the anchor nodes in a proper way, and the mobile station has been restricted to move through a harsh environment. Then, we use the linearized LS to locate the mobile station and evaluate the positioning accuracy by implementing the proposed MSE, and a proposed algorithm named AS is used to select the anchor group providing the best positioning accuracy and relocate the mobile with the selected group using the WLS method. The linearized LS and WLS are implemented to avoid the initial guess point and the iteration that should be used in the non-linear LS method, so the computation time of the mobile location is reduced. Also, the proposed MSE will be computed with less complexity in the linearized LS. Estimating a positioning node in two-dimensions acquires range information from at least three anchors. In this model and for simplicity, we provide

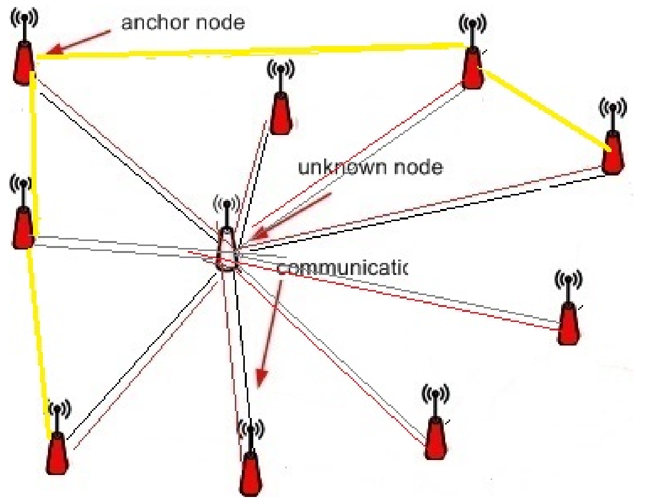

Fig. 1. The system model that has n number of anchor nodes and one mobile station(should be in any direction in the plane). and distance measurements have different errors. The yellow line denotes the $\hat{n} = 2, 3, ... < n$ selected anchor nodes.

an analysis of two dimensional localization. Let $h = [x; y]$ presents the mobile station position in Cartesian coordinates x and y. Also, $A_i = [x_i; y_i]$ denotes Anchor nodes positions. $i = 1, ...\hat{n}$ denotes the index of the anchor node and $\hat{n}$ denotes the number of the entire optimum anchor nodes. Then, we can compute the Euclidean (real) distance (r) between h and A in a generic way.

$$r_i^2 = ||x_i - x||^2 = (x_i - x)^2 + (y_i - y)^2 \tag{1}$$

A localization algorithm should be applied once the distances (r) to different anchor nodes are measured to calculate the position of the mobile node. The simplest and most common positioning algorithm that has been used for RSS-based localization is the hyperbolic positioning algorithm [20, 21]. As we explained above, r denotes the real distance and let denote the measured distance extracted from the sensor as $\hat{r}$ then the error is computed as

$$\epsilon = \sum_{i=1}^{n} (r_i - \hat{r_i}) \tag{2}$$

The estimated position can be calculated iteratively by implementing a straight gradient method for an example.

$$\hat{h} = \begin{bmatrix} \hat{x} \\ \hat{y} \end{bmatrix}_{k+1} = \begin{bmatrix} \hat{x} \\ \hat{y} \end{bmatrix}_{k} - \alpha \begin{bmatrix} \frac{\partial \epsilon}{\partial x} \\ \frac{\partial \epsilon}{\partial y} \end{bmatrix}_{x=\hat{x}_k, y=\hat{y}_k} \tag{3}$$

where α is a scalar selected to minimize ϵ. Also, $\hat{x}$ and $\hat{y}$ the estimated coordinates of the MS. In this method, an initial value of the position estimation is needed. To convert this non linear into a linear problem, the hyperbolic positioning algorithm is used by implementing least square method [19] as we presented in the next subsection.

A. L S linearization

To linearize the LS solution, one of the equations in the group of the equations in Eq.1 is selected as a reference equation and subtract it from all other equations in the system. For simplicity, we state A_1 as a reference node having $x_1 = y_1 = 0$, so

$$r_1^2 = x^2 + y^2 \tag{4}$$

Then the linearization problem will be

$$r_1^2 - r_i^2 = x^2 + y^2 - ((x_i - x)^2 + (y_i - y)^2) \tag{5}$$

Where, $i = 1.........n$
By modifying Eq.5, we obtain Eq.6 as written below

$$x_i^2 + y_i^2 + r_1^2 - r_i^2 = 2xx_i + 2yy_i \tag{6}$$

Then converting Eq.6 to matrix notation, we can obtain

$$A = \begin{bmatrix} 2x_2 & 2y_2 \\ 2x_3 & 2y_3 \\ \vdots & \vdots \\ 2x_n & 2y_n \end{bmatrix}$$

$$b = \begin{bmatrix} x_2^2 + y_2^2 + r_1^2 - r_2^2 \\ x_3^2 + y_3^2 + r_1^2 - r_3^2 \\ \vdots \\ x_n^2 + y_n^2 + r_1^2 - r_n^2 \end{bmatrix} = \begin{bmatrix} b_2 \\ b_3 \\ \vdots \\ b_n \end{bmatrix}$$

where, r_1 denotes the real distance between the reference node and mobile station and r_i denotes the distance between mobile station and all nodes except the reference. Finally, the mobile station coordinates h will be computed as shown in Eq.7

$$h = \begin{bmatrix} x \\ y \end{bmatrix} = (A^T A)^{-1} A^T b \tag{7}$$

As mentioned in Eq.7, at least three distance measurements will be needed to obtain a solution using the LS method. However, it is not always installing more anchor nodes in the network means that we obtain a good IP system. In some cases, we could have a better positioning system with only two anchor nodes as shown in figure 2. So, the solution presented in this work is to involve virtual anchor nodes in the LS method instead of the worst measured distance. With two anchor nodes, only two equations are available to guess the x and y coordinates. However, two equations provide two possible solutions and, if we know how to resolve the ambiguity by some extra information such as to locate the mobile position using three anchor nodes then replacing the node that provides worst distance estimation by the virtual distance so the LS could be used for unifying the MSE method for group two or more anchor nodes.
The next subsection explains the virtual distance.

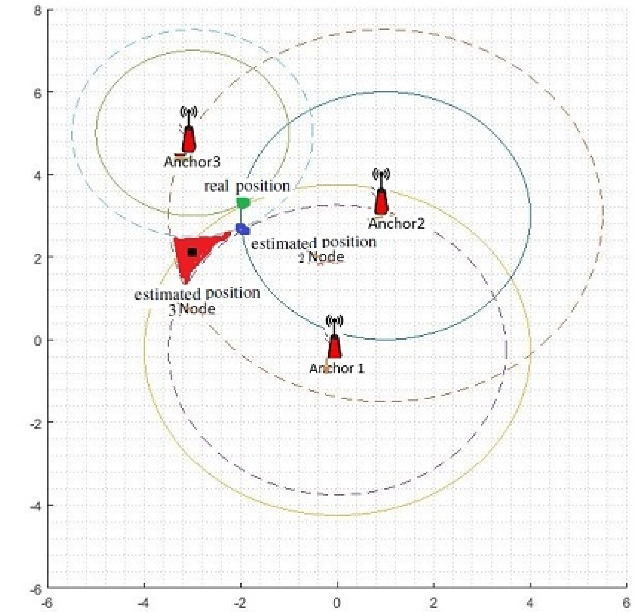

Fig. 2. Two and three anchor nodes having different distance error to the mobile station when the localization system with two anchor nodes provides better accuracy.

B. *Virtual distance*

As stated before, The two anchor nodes system could be in some states provide better positioning accuracy. Such a system also will be involved in the MSE and the AS algorithms using the virtual node. Thus, we can unify the proposed MSE to extend the selection of anchor node by also selecting two anchor nodes system. Figure. 3 depicts the creation of the virtual distance d_v and all variables mentioned in Eq.8. The Virtual node could be fixed in any place in the space. Then, it is computed using the triangle rules as shown below.

$$d_v = \sqrt{d_1^2 + d_{ava1}^2 - 2d_1 d_{ava1} cos(\theta)} \tag{8}$$

Where, θ could be $\beta - A1$ or $\beta + A1$ according to the mobile station position located previously.

,

$$\beta = cos^-1(\frac{d_{a2a1}^2 + d_{ava1}^2 - d_{ava2}^2}{2d_{a2a1}d_{ava1}})$$

, and

$$A1 = cos^-1(\frac{d_{a2a1}^2 + d_2^2 - d_1^2}{2d_{a2a1}d_{ava1}})$$

The next section presents the MSE derivation.

IV. MSE COMPUTATION IN LINEARIZED LS

In this section, the MSE is achieved by the linearized LS solution explained in section III when the true value of the mobile position is unknown.

In this work, the solution of LS method is considered for the best linear unbiased estimator (BLUE) when n anchor nodes distributed in an environment to locate a mobile station as

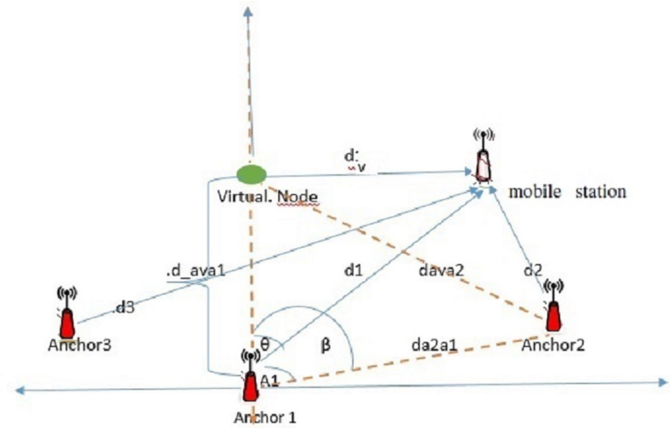

Fig. 3. Virtual node and its distance to the mobile station.

aforementioned in the anchor selection section.

The MSE could be written in a generic way as shown in Eq.9

$$MSE = \mathbf{E}\left\{ \left\|\hat{h} - h\right\|^2 \right\} = \mathbf{E}\left\{\hat{h}^T\hat{h}\right\} - 2\mathbf{E}\left\{\hat{h}^T\right\}h + h^T h \tag{9}$$

where h and $\hat{h}$ denote the real and estimated position of the MS respectively. Also, Eq.7 in section III can be split into two parts as shown below:

The first part of Eq.7 ($(A^T A)^{-1}$) is only deterministic data (the coordinates of the anchor nodes) and therefore, implementing matrix operation to it, we obtain a new matrix of 2 by 2 as shown below when we denoted it as V.

$$V = \begin{bmatrix} v_{11} & v_{12} \\ v_{21} & v_{22} \end{bmatrix}$$

where,

$$v_{11} = 0.25\frac{(y_2^2 + y_3^2 + ...y_n^2)}{(y_2^2 + y_3^2 + ...y_n^2)(x_2^2 + x_3^2 + ...x_n^2) - (x_2y_2 + x_3y_3 + ...x_ny_n)^2}$$

$$v_{12} = -0.25\frac{(x_2y_2 + x_3y_3 + ...x_ny_n)}{(y_2^2 + y_3^2 + ...y_n^2)(x_2^2 + x_3^2 + ...x_n^2) - (x_2y_2 + x_3y_3 + ...x_ny_n)^2}$$

$$v_{22} = 0.25\frac{(x_2^2 + x_3^2 + ...x_n^2)}{(y_2^2 + y_3^2 + ...y_n^2)(x_2^2 + x_3^2 + ...x_n^2) - (x_2y_2 + x_3y_3 + ...x_ny_n)^2}$$

and $v_{21} = v_{12}$

Also implementing matrix operation to the second part of Eq.7 ($A^T b$) will be

$$A^T b = \begin{bmatrix} \sum_{i=2}^{n} 2x_i bi \\ \sum_{i=2}^{n} 2y_i bi \end{bmatrix} \tag{10}$$

where, $b_i = x_i^2 + y_i^2 + r_1^2 - r_i^2$
Then, the Eq.7 in section III is rearranged to be

$$h = \begin{bmatrix} v_{11}\sum_{i=2}^{n} 2x_i bi + v_{12}\sum_{i=2}^{n} 2y_i bi \\ v_{21}\sum_{i=2}^{n} 2x_i bi + v_{22}\sum_{i=2}^{n} 2y_i bi \end{bmatrix} \tag{11}$$

To start solving Eq.9, we solve each part of it individually then combine them. First and for simplicity, let us denote the first, second , and third part of it as:

$p1 = \mathbf{E}\Big\{\hat{h}^T\hat{h}\Big\}$

$p2 = \mathbf{E}\Big\{\hat{h}^T\Big\}h$

$p3 = h^T h$

So, Eq 9. could be rewritten as

$$MSE = p1 - 2p2 + p3 \tag{12}$$

For simplicity, we move all mathematical steps of the proposed MSE to appendix 1.
Then, The performance in terms of MSE achieved is

$$MSE = \begin{bmatrix} v_{11}^2 + v_{21}^2 \\ v_{12}^2 + v_{22}^2 \\ 2v_{11}v_{12} + 2v_{21}v_{22} \end{bmatrix}^T \begin{bmatrix} \mathbf{E}\Big\{[\sum_{i=2}^{n} 2x_i \bar{\mathbf{b}}_i]^2\Big\} \\ \mathbf{E}\Big\{[\sum_{i=2}^{n} 2y_i \bar{\mathbf{b}}_i]^2\Big\} \\ \mathbf{E}\Big\{\sum_{i=2}^{n} 2x_i \bar{\mathbf{b}}_i \sum_{i=2}^{n} 2y_i \bar{\mathbf{b}}_i\Big\} \end{bmatrix} \tag{13}$$

Proof: see the Appendix.
To implement the proposed MSE method, we should clarify that the only input variable of the MSE function is the real distance (r). But, in a real experiment when we don't have it, we implement proper NLOS identification and mitigation method created by [11]. In addition to the aforementioned method of NLOS identification, we created a database as shown in table I to estimate the average distance error in hard and soft NLOS and LOS propagation channels to enhance the measured distance as shown in Eq.14 below

$$\acute{r} = \hat{r} - \varepsilon(e) \simeq r \tag{14}$$

where, $\acute{r}$, $\hat{r}$, $\varepsilon(e)$, and r denote the approximated real distance, measured distance, the average distance error, and the real distance respectively. So, the approximated real distance ($\acute{r}$) is used in the MSE method instead of the real distance (r) and also used in all positioning methods used in this work.

V. Anchor Selection (AS)

The proposed IP system which is an online selection of a group of two anchor nodes or more up to $\hat{n}$ anchor nodes using MSE evaluation method is explained below.
For a generic scenario of IP system dealing with UWB signal, we may install n nodes in the WSN and we could select $\hat{n} < n$ using the RSL. In this work, we consider a real environment with 6 UWB sensors covering an area of 9 m^2: one sensor as a tag and the remaining five sensors installed as anchor nodes. According to our experience, positioning accuracy is not significantly improved when a large number of anchor nodes is available and usually 4 to 6 anchor nodes provides a good compromise. Then, the 5 nodes are clustered into different groups according to the combination algorithm. So the total number of groups $=\binom{\hat{n}}{2} + \binom{\hat{n}}{3} + ... + \binom{\hat{n}}{\hat{n}}$
where n and $\hat{n}$ are the total number of the anchor nodes installed in the entire network and the total number of selected anchors (in this work $\hat{n} = 5$) installed to build the positioning system.
The RSL is extracted from the UWB device (DW 1000 - EVK 1000) used in this work. It indicates the level of the received signal power provided by an anchor node [30]. It is chosen in this work as criteria to select the optimum anchor nodes ($\hat{n}$) selected for the combination process. The total number of the anchor nodes used in this work (5 anchor nodes) is not large, and it is not so important, and therefore it does not depend on how large the network (n anchor nodes).
Also, every group should have a reference node. We locate the mobile station using the conventional LS method then evaluate the positioning accuracy of each group of anchor nods using the derived MSE and select the group having less MSE and removing all other anchor groups from the positioning system to relocate the mobile station using WLS algorithm. The algorithm 1 depicts the steps of the proposed algorithm. The next section provides the experimental results of the LS, WLS, and MLSI (before anchor selection), and AS localization algorithms.

VI. Experimental and Evaluation Activities

In this section, we provide experimental results obtained with a commercial UWB device (DW 1000-EVK 1000). The DW 1000 is a fully integrated low-power, multichannel single-chip CMOS radio transceiver that meets the IEEE 802.15.4-2011 ultra-wideband (UWB) standard [30].
Before starting with the experimental activities, we start with the evaluation process of the derived MSE and an overview of the WLS and MLSI methods as explained in the next items.

A. Evaluation of the derived MSE and an overview of WLS and MLSI

The items below explains the process of the evaluation method used for evaluating the derived MSE and provides an overview of the WLS and MSLI methods used to be compared with the proposed IP system (AS).

- Evaluation of the derived MSE
  After computing the MSE, it is compared with MSE Matlab function using a rational error as shown in Eq.15 to ensure the accuracy of the mathematical derivation. Figures 4 and 5 show the value of the derived MSE compared to MSE Matlab function of a mobile positioning

Algorithm 1 Anchor Selection (AS)

procedure ANCHOR GROUP ▷ Create different anchor node groups
  $\hat{n} \leftarrow n$ ▷ The total anchor nodes
  for $i = 2$ to $\hat{n}$ **do**
    Anchor group=$\binom{\hat{n}}{i}$
    $m = \sum_i^{\hat{n}} \binom{\hat{n}}{i}$ ▷ the total anchor groups
  end for
end procedure
procedure LS ▷ Locate the mobile station

$$\hat{h} = (A^T A)^{-1} A^T \hat{b}$$

end procedure
procedure MSE ▷ Compute MSE for each group
  for $i = 1$ to m **do**

$$MSE = \mathbf{E}\left\{ \left\| \hat{h(i)} - h(i) \right\|^2 \right\}$$

  end for
end procedure
procedure AS ▷ Select the group having minimum MSE
  for $i = 1$ to m **do**

$$MSE = \mathbf{min}\left\{ MSE(i) \right\}$$

  end for
end procedure
procedure WLS
▷ Compute the variance of the estimated distance
▷ Relocate the Mobile station

$$\hat{h} = (A^T W^{-1} A)^{-1} A^T W^{-1} \hat{b}$$

end procedure

for 14 different mobile positions and the rational error between them respectively.

$$E = \frac{MSE_{dir} - MSE}{MSE} 100\% \qquad (15)$$

where, E, MSE_{dir}, and MSE denote the rational error, proposed MSE, and MSE of matlab function respectively.

- Weighted least square (WLS).
  To validate the anchor selection system model, it is compared to the conventional LS and also, to the WLS and MLSI algorithms created by [19] and [33] respectively. A short overview of the WLS and MLSI algorithms is presented below.
  The liner equation in Eq.7 could be solved implementing a weighted least-square estimator as shown in Eq.16 below.
  The weights implemented in the WLS algorithm is adjusted taking into account the inverse of the variance of the corresponding distance measurements [19]. The DW 1000 (EVK 1000) device provides 8 distance measurements per second and therefore, we calculate and update the variance every one second and calculate the matrix of it (W) which is the covariance matrix of vector $\hat{b}$ as aforementioned below, then using the inverse of it in the final equation of the WLS as shown in Eq.16.

$$W = \begin{bmatrix} var(\acute{r}_1{}^2) + var(\acute{r}_2{}^2) & var(\acute{r}_1{}^2)... & var(\acute{r}_1{}^2) \\ var(\acute{r}_1{}^2) & var(\acute{r}_1{}^2) + var(\acute{r}_3{}^2)... & var(\acute{r}_1{}^2) \\ & \vdots & \\ var(\acute{r}_1{}^2) & var(\acute{r}_1{}^2)... & var(\acute{r}_1{}^2) + var(\acute{r}_n{}^2) \end{bmatrix}$$

where $var(\hat{r}_1{}^2)$ denotes the variance of a squared estimated distance between the reference node and mobile station, and $var(\hat{r}_i{}^2)$ denotes variance of a squared estimated distance between all other nodes and the mobile station.

$$\hat{b} = \begin{bmatrix} x_2^2 + y_2^2 + \acute{r}_1{}^2 - \acute{r}_2{}^2 \\ x_3^2 + y_3^2 + \acute{r}_1{}^2 - \acute{r}_3{}^2 \\ \vdots \\ x_n^2 + y_n^2 + \acute{r}_1{}^2 - \acute{r}_n{}^2 \end{bmatrix}$$

.

$$\hat{h} = \begin{bmatrix} \hat{x} \\ \hat{y} \end{bmatrix} = (A^T W^{-1} A)^{-1} A^T W^{-1} \hat{b} \qquad (16)$$

Presuming that the distance measurements $\hat{b_i}$ to different nodes are independent and x_i and y_i are constant.

- Modified least square iteration (MLSI) method.
  The MLSI method has the same mathematical expression of the conventional LS (Eq.7) with modifying the distance vector ($\hat{b}$) by involving the average distance error to it

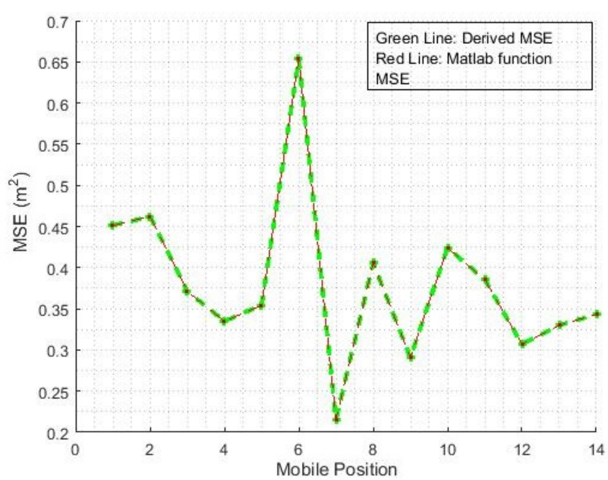

Fig. 4. Values of the proposed MSE and matlab functions.

as shown below.
First, let $\varepsilon(e_1)$ and $\varepsilon(e_i)$ denote the average distance error between the MS and the reference node and the average distance error between the MS and the rest of the entire anchor nodes respectively where $i = 2, ...n =$ Then:

$$\hat{b}_i = x_i^2 + y_i^2 + \acute{r_1}^2 - \acute{r_i}^2 + \varepsilon(e_1) - \varepsilon(e_i)$$

Or

$$\hat{b} = \begin{bmatrix} x_2^2 + y_2^2 + \acute{r_1}^2 - \acute{r_2}^2 + \varepsilon(e_1) - \varepsilon(e_2) \\ x_3^2 + y_3^2 + \acute{r_1}^2 - \acute{r_3}^2 + \varepsilon(e_1) - \varepsilon(e_3) \\ \vdots \\ x_n^2 + y_n^2 + \acute{r_1}^2 - \acute{r_n}^2 + \varepsilon(e_1) - \varepsilon(e_n) \end{bmatrix}$$

.

B. Experimental activities

In this part of the work, different scenarios are created to examine the proposed method used for a moving target in different directions and distances to the installed anchor nodes. We randomly installed the anchor nodes as shown in figure 7 inside a narrow squared area of 9 m side within the total moving area of 16 m width and 25 m length. Figure 8 presents scenario 1 for a trajectory of the mobile station created using the AS, MLSI, and WLS algorithms. Figure 9 presents scenario 2 for a different trajectory created by the AS, WLS, and LS. The AS algorithm with a suitable anchor group for every point in the trajectory. The MLSI with the four and five anchor nodes group. The WLS and LS algorithms with the group of five anchor nodes for the entire trajectory. The coordinates of the anchor nodes in the two different scenarios as follows:
Scenario 1 :A_1 = (0; 0), A_2 = (1;7.8), A_3 = (2;7.8), A_4 = (2.6; 1.4), and A_5 = (3;1.6) as shown in figure 8.
Scenario 2 :A_1 = (0; 0), A_2 = (2;4.8), A_3 = (4;4.8), A_4= (7.6; 4.4), and A_5 = (3;1.6). as shown in figure 9.

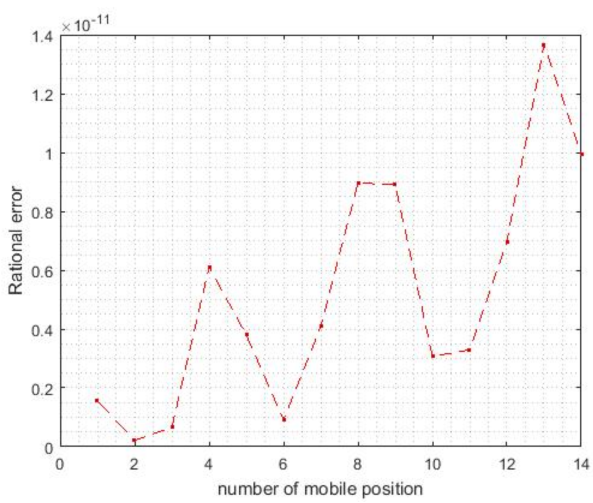

Fig. 5. Rational error between the derived and matlab MSE functions.

where A_i denotes the anchor node in the network. The estimated distances between anchor nodes and the mobile station are extracted from the EVK 1000 device. To build the proposed IP system by implementing the AS method, we implemented a proper NLOS identification method [11] and created table I to estimate the average distance bias. Then, Eq.14 is used to obtain the approximated real distance for the proposed MSE to evaluate the positioning accuracy of different groups of anchor nodes (including the virtual nodes group), and select the group having the less MSE, then relocated the mobile station with the selected group using the WLS method. In this work, the distance measurement is extracted from the EVK 1000. It is a transceiver sensor uses two-way time of flight to compute the distance between two transceivers, and it is a Bias estimator in a LOS environment according to [25, 26, 27] so we should overcome this issue to cope with the proposed linear MSE method. So, we applied an algorithm presented by [29] to modify the EVK 1000 having the BLUE specifications in a LOS environment. This algorithm is to place two EVKs 1000 with 8 m apart in between inside a LOS environment and take at least 400 times of distance measurements then compute the average error between the true and estimated values then apply Eq.17 below to obtain a new estimated distance by reprogramming EVK 1000, and Table I shows that modified EVK 1000 is a BLUE estimator.

$$e_{av} = d_{real} - d_{est}$$
$$d_{new} = d_{est} + e_{av} \tag{17}$$

where, the d_{real}, d_{new}, d_{est}, e_{av}, are the real distance, new estimated distance, average of old estimated distance, and the average of the computed error experimentally for 8 m distance. The transceivers were randomly distributed in the environment presented in fig.6 as shown in fig.7.
In [11], we estimated the error of a measured distance of a walking human in an indoor environment having different channel types (LOS, soft NLO, and hard NLOS) using UWB technology (DW1000, EVK 1000). The estimated error of the distance from 2 m to 26 m ranges between 0.3 m to 1.8 m depends on the traveled distance and number of walls that may affect the measured distance.
In this work, we restricted the mobile station to move through

Fig. 6. The real environment.

one and two concert walls 30 cm width each (soft and hard NLOS channels) and through LOS channel using channel 2 mode 2 of DW 1000 (EVK 1000) [23, 11]. Also, in [11], the ch 2 mode 2 of EVK 1000 was experimentally validated for obtaining ranging measurements.

To place a wireless sensor in a network, an area should be taken into consideration called a Fresnel zone (FZ) around the visual line of sight that radio waves spread out into after they leave the antenna [24]. The FZ must be clear to avoid the weak in the signal strength level.

Then, we measured the distances and computed the related average error to eliminate the bias in the distance and compute the approximated real distance used in the MSE evaluation method.

The ranging measurements are used in different environments (LOS, soft NLOS, and hard NLOS) for distance ranges from 2 m to 20 m. Table I presents the information used for the AS algorithm extracted from the modified EVK 1000.

TABLE I
DISTANCE MEASUREMENT WHERE, r,$\hat{r}$, AND Var DENOTE THE REAL, ESTIMATED, AND VARIANCE OF DISTANCE RESPECTIVELY FOR LOS, SOFT NLOS, AND HARD NLOS CHANNELS AND Av DENOTES THE AVERAGE OF THE DISTANCE BIAS

	LOS			HNLOS			SNLOS		
$r(m)$	$\hat{r}(m)$	Bias (m)	Var (m^2)	$\hat{r}(m)$	Bias (m)	Var (m^2)	$\hat{r}(m)$	Bias (m)	Var (m^2)
2	2.09	0.09	0.00	–	–	–	–	–	–
4	4.09	0.09	0.00	–	–	–	4.20	0.16	0.06
6	6.02	0.02	0.01	–	–	–	6.3	0.26	0.10
8	8.05	0.05	0.08	9.33	1.33	0.01	8.28	0.27	0.07
10	10.06	0.06	0.00	10.74	0.74	0.08	10.12	0.12	0.11
12	12.000	0.00	0.01	12.59	0.59	0.07	12.10	0.10	0.04
14	14.00	−0.06	0.00	15.00	1.00	0.09	14.505	0.51	0.07
16	16.05	0.05	0.00	16.95	0.95	0.05	16.36	0.36	0.06
18	18.02	0.02	0.00	18.47	0.47	0.12	18.24	0.244	0.10
20	20.07	0.07	0.00	20.70	0.70	0.14	20.50	0.50	0.12
Av Bias	–	0.052	–	–	0.822	–	–	0.279	–

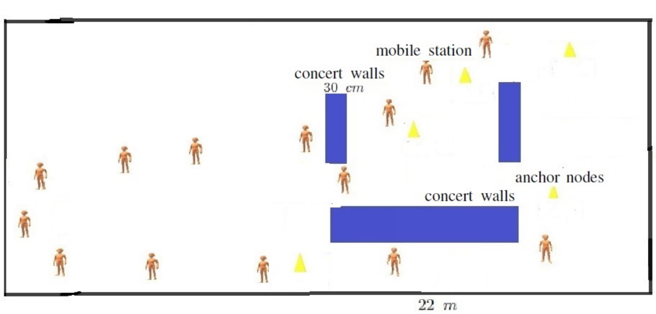

Fig. 7. Simulation of the moving target in real environment (one of different scenarios) that will be located using different distance measurement affect by different walls.

VII. RESULTS AND DISCUSSION

In the experimental activity, Different Mobile station trajectories have been created to measure the estimated distance having different distance errors then the average and variance of it used for the AS and WLS algorithms are computed.

As mentioned before, we assume a proper NLOS identification method is used to extract the average distance bias as shown in Table I used to enhance the approximated distance computed in Eq.14 to compute the proposed MSE to evaluate the LS method. For special cases in the NLOS propagation channels, It is observed; when placing a transceiver opposite to a wall with distance less than 1.3 m, the distance error increased abnormally to approximately 1 m. This abnormal increment in distance error is due to the high attenuation of the UWB signal when placing or moving the sensors close to a wall. This problem should be taken into consideration when using an NLOS identification and mitigation method.

In this work, the results plot trajectories of the mobile node but, at every point in the trajectory, the position is computed without taking into account node dynamics. Only, the last known position is used to obtain the estimated distances to the anchors in order to feed the anchor selection algorithm. The AS is compared to the LS, WLS, MLSI, and GDOP methods as shown in figure 9 which presents the empirical cumulative distribution function (ECDF) of the trajectory presented in scenario 1 (figure 8), and figure 11 presents the same information provided in figure 9 but for the scenario 2 (figure 10). As we mentioned in the titles of figures 7, The AS is implemented for different groups of anchor nodes according to the proposed MSE method and therefore, the points may be located by 2,3,...$\hat{n}$ anchor nods. But, the WLS and LS methods are implanted with $\hat{n}$ anchor nodes.Also, the MLSI and GDOP methods are implemented with $\hat{n}$ anchor nodes (in this work $\hat{n}$ = 5 nodes).

As we mentioned above in the abstract of this paper about GDOP, we address some drawbacks that impact the indoor positioning accuracy. First, we should address that IPs usually have irregular propagation models and barriers that complicate deployment, making it defy to specify a metric to readily compare anchor configuration. GDOP is a unit-less quantity which is a function of the geometry between the target and the beacons, often utilized to estimate the expected accuracy of GPS due to the location of satellites [34]. GDOP has three main drawbacks when utilized as a metric for assessing indoor accuracy. First, Some circumstances cause the standard GDOP metric to expand towards infinity which makes it difficult to normalize over multiple competing configurations [31]. Second, For a terrestrial system, if the location and number of base stations in the desired coverage area are not neatly planned, the GDOP effect can become the dominant factor in limiting the performance of a system [32]. Third, theoretically, the more the nodes involved in the calculation, the lower the GDOP value of the combination will be, which represents a higher positioning accuracy. Also, In the traditional GDOP-based nodes selection algorithm, n nodes will be selected from m anchor nodes, and therefore in order to select a subset which has the smallest GDOP, matrix multiplication and inversion should be executed for a combination of m to n times [18]. Finally, some accuracy results are provided to have a reference about performance obtained with GDOP. For instance, the best positioning accuracy obtained in [18] is around 1 m when 10 anchor nodes are involved in the system. Another example of GDOP is presented in [20], where it is assumed that there is no mobile target but all anchor nodes will act as mobile units. In that work, 36 nodes are considered and a positioning accuracy around half meter is obtained. For the sake of comparison, we also include results corresponding to the GDOP strategy proposed in [20] in Fig. 9. In particular, this figure presents the ECDF of MSE of MLSI, WLS, AS, and GDOP and shows how the technique derived in this work outperforms the other methods.

The result of figures 9 and 11 experimentally show that the proposed method significantly improves the localization accuracy, reducing the estimation error between 60% and 95% on average, compared with the existing approaches. The results presented in this section clearly show how the AS method is confident in different indoor scenarios including emergency.

VIII. Conclusion

The cost in term of installation time and the number of wireless sensors in an indoor environment and precisely locate a moving target are the goals of this work. To obtain this goal, we present a novel algorithm of three steps:i- create online an MSE using the linearized LS to dynamically evaluate the positioning accuracy of the IP system created by different groups of anchor nodes. ii- Select the group having the best accuracy (AS) and relocate the mobile station using the WLS. iii- Involve the virtual node to enable the LS working with only two anchor nodes when needed for the MSE. The work

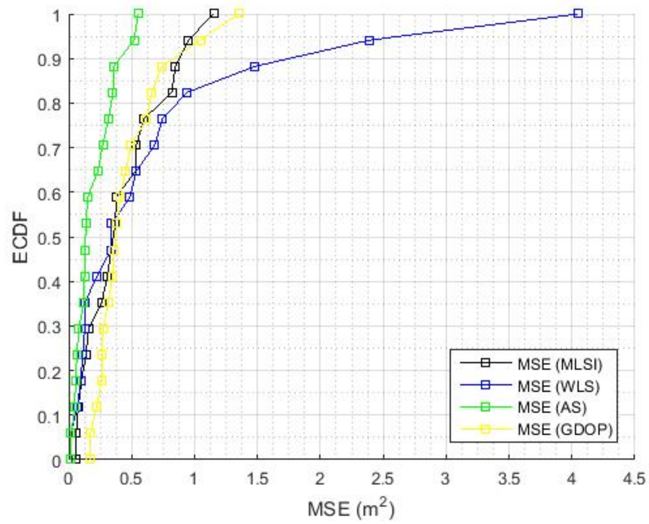

Fig. 9. Empirical distributed function (ECDF) of AS, MLSI, WLS, and GDOP methods in scenario 1.

done with experiment phase presents an evidence using the AS can reach an accurate IP system with less than 0.5 m^2 of MSE of a positioning and less installation time and number of wireless sensors in a harsh environment while the WLS, MLSI, GDOP, and LS algorithms reach more than 3.5 m^2, 1.2 m^2, 1.4 m^2, and 9 m^2 of MSE respectively. The proposed method provides a highly an accepted localization accuracy for different scenarios including emergency.

Appendix A
MSE derivation

In this Appendix, we present the entire derivation of MSE.

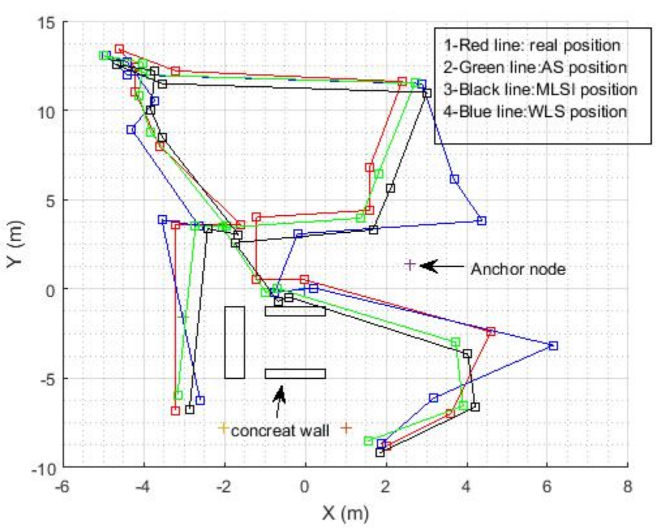

Fig. 8. Scenario 1: simulation of the moving target in real environment (one of different scenarios) affected by different walls and will be located using AS, MLSI, and WLS localization algorithm.

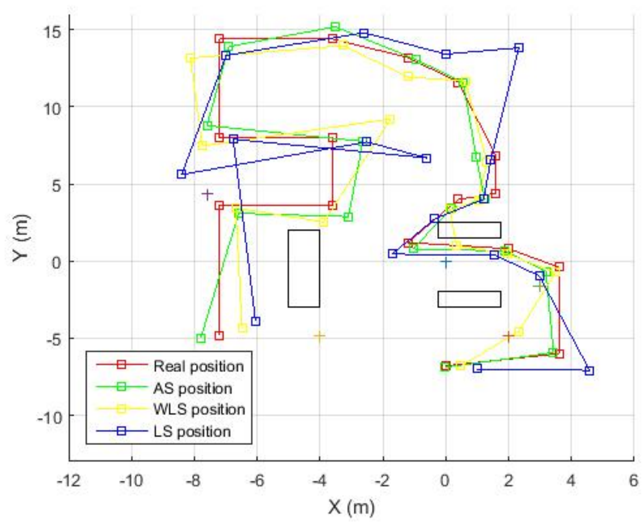

Fig. 10. Scenario 2: simulation of the moving target in real environment (one of different scenarios) affected by different walls and will be located using AS, WLS, and LS localization algorithm.

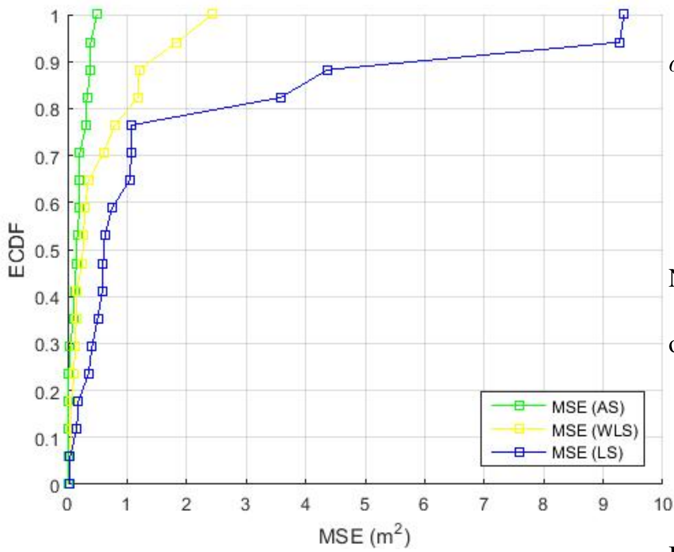

Fig. 11. Empirical distributed function (ECDF) of AS, WLS, and LS methods in scenario 2.

AS we mentioned in MSE computation section above, the MSE could be written as shown in Eq. 12 and below

$$MSE = p1 - 2p2 + p3 \tag{1}$$

So, we solve every part of Eq.1 separately then collect them to obtain the final mathematical expression of the derived MSE. First, we start with $p3$,

$$p3 = \Bigg[v_{11}\sum_{i=2}^{n} 2x_i bi + v_{12}\sum_{i=2}^{n} 2y_i b_i\Bigg]^2 + \Bigg[v_{21}\sum_{i=2}^{n} 2x_i bi + v_{22}\sum_{i=2}^{n} 2y_i bi\Bigg]^2$$

Furthermore, only the first part of $p3$ is solved because the second part is similar and the difference is only with v values which is constant. The first and second part of it are denoted by $p3_1$ and $p3_2$ respectively and starting to solve $p3_1$

$$p3_1 = v_{11}^2\Big[\sum_{i=2}^{n} 2x_i b_i\Big]^2 + 2v_{11}v_{12}\sum_{i=2}^{n} 2x_i b_i \sum_{i=2}^{n} 2y_i b_i + v_{12}^2\Big[\sum_{i=2}^{n} 2y_i b_i\Big]^2$$

Second, the other parts ($p1$ and $p2$) in Eq.1 are computed. So, b should be changed to $\hat{b}$.

$$\hat{b} = \begin{bmatrix} x_2^2 + y_2^2 + \hat{d_1}^2 - \hat{d_2}^2 \\ x_3^2 + y_3^2 + \hat{d_1}^2 - \hat{d_3}^2 \\ \vdots \\ x_n^2 + y_n^2 + \hat{d_1}^2 - \hat{d_n}^2 \end{bmatrix}$$

where, $\hat{b_i} = x_i^2 + y_i^2 + \hat{d_1}^2 - \hat{d_i}^2$,

$\hat{d_1} = r_1 + e_1 \rightarrow \hat{d_1}^2 = r_1^2 + 2e_1r_1 + e_1^2$

and, $\hat{d_i} = r_i + e_i \rightarrow \hat{d_i}^2 = r_i^2 + 2e_ir_i + e_i^2$ Then substituting $\hat{d_1}^2$ and $\hat{d_i}^2$ in $\hat{b}$, to obtain

$$\hat{b} = \begin{bmatrix} x_2^2 + y_2^2 + r_1^2 + 2e_1r_1 + e_1^2 - r_2^2 + 2e_2r_2 - e_2^2 \\ x_3^2 + y_3^2 + r_1^2 + 2e_1r_1 + e_1^2 - r_3^2 + 2e_3r_3 - e_3^2 \\ \vdots \\ x_n^2 + y_n^2 + r_1^2 + 2e_1r_1 + e_1^2 - r_n^2 + 2e_nr_n + e_n^2 \end{bmatrix}$$

Now, let denote

$\bar{\mathbf{b}}_i = e_1^2 - e_i^2 + 2r_1e_1 + 2r_ie_i$. Then, the expectation value of $\hat{b}$ is written as

$$\mathbf{E}\{\hat{b}\} = \mathbf{E}\Bigg\{\begin{bmatrix} b_2 + \bar{\mathbf{b}}_2 \\ b_3 + \bar{\mathbf{b}}_3 \\ \vdots \\ b_n + \bar{\mathbf{b}}_n \end{bmatrix}\Bigg\}$$

In Eq.1, the difference between $p1$ and $p3$ is only the notation of the expectation value which is expressed in $p1$. Thus, solving $p1$ will be in the same way of solving $p3$ with taking into account the expectation notation. Also, we denote the first part of $p1$ as $p1_1$ and the second part $p1_2$. For the similarity in $p1_1$ and $p1_2$, we solve only $p1_1$.

$$p1_1 = v_{11}^2\mathbf{E}\Bigg\{\Big[\sum_{i=2}^{n} 2x_i(b_i + \bar{\mathbf{b}}_i)\Big]^2\Bigg\} + 2v_{11}v_{12}\mathbf{E}\Bigg\{\sum_{i=2}^{n} 2x_i(b_i + \bar{\mathbf{b}}_i)\sum_{i=2}^{n} 2y_i(b_i + \bar{\mathbf{b}}_i)\Bigg\} + v_{12}^2\mathbf{E}\Bigg\{\Big[\sum_{i=2}^{n} 2y_i(b_i + \bar{\mathbf{b}}_i)\Big]^2\Bigg\}$$

Now, we analyze

$$v_{11}^2\mathbf{E}\Bigg\{\Big[\sum_{i=2}^{n} 2x_i(b_i + \bar{\mathbf{b}}_i)\Big]^2\Bigg\}$$

to obtain

$$v_{11}^2\mathbf{E}\Bigg\{\Big[\sum_{i=2}^{n} 2x_i(b_i + \bar{\mathbf{b}}_i)\Big]^2\Bigg\} = v_{11}^2\Big[\sum_{i=2}^{n} 2x_i b_i\Big]^2 + 2v_{11}^2\sum_{i=2}^{n} x_i b_i \mathbf{E}\Big\{\sum_{i=2}^{n} 2x_i\bar{\mathbf{b}}_i\Big\} + v_{11}^2\mathbf{E}\Bigg\{\Big[\sum_{i=2}^{n} 2x_i\bar{\mathbf{b}}_i\Big]^2\Bigg\}$$

Also, by the same way, we obtain

$$v_{12}^2\mathbf{E}\Bigg\{\Big[\sum_{i=2}^{n} 2y_i(b_i + \bar{\mathbf{b}}_i)\Big]^2\Bigg\} = v_{12}^2\Big[\sum_{i=2}^{n} 2y_i b_i\Big]^2 + 2v_{12}^2\sum_{i=2}^{n} 2y_i b_i \mathbf{E}\Big\{\sum_{i=2}^{n} 2y_i\bar{\mathbf{b}}_i\Big\} + V_{12}^2\mathbf{E}\Bigg\{\Big[\sum_{i=2}^{n} 2y_i\bar{\mathbf{b}}_i\Big]^2\Bigg\}$$

the last part needed to analyze is

$$2v_{11}v_{12}\mathbf{E}\Bigg\{\sum_{i=2}^{n}2x_i(b_i+\bar{\mathbf{b}}_i)\sum_{i=2}^{n}2y_i(b_i+\bar{\mathbf{b}}_i)\Bigg\}=$$

$$2v_{11}v_{12}\sum_{i=2}^{n}2x_ib_i\sum_{i=2}^{n}2y_ib_i+2v_{11}v_{12}\mathbf{E}\Big\{\sum_{i=2}^{n}2x_ib_i\sum_{i=2}^{n}2y_i\bar{\mathbf{b}}_i\Big\}$$
$$+2v_{11}v_{12}\mathbf{E}\Big\{\sum_{i=2}^{n}2y_ib_i\sum_{i=2}^{n}2x_i\bar{\mathbf{b}}_i\Big\}$$
$$+2v_{11}v_{12}\mathbf{E}\Big\{\sum_{i=2}^{n}2x_i\bar{\mathbf{b}}_i\sum_{i=2}^{n}2y_i\bar{\mathbf{b}}_i\Big\}$$

Then using the same way, we can find $p3_2$ and $p1_2$ and compute

$$p3_2+p3_1=p3$$
$$p1_2+p1_1=p1$$

Finally, compute the last part of Eq.1, $p2$ and split it into two parts which will be denoted $p2_1$ and $p2_2$ respectively, also, we can compute one of them. We are computing $p2_1$.

$$p2_1=v_{11}^2\Big[\sum_{i=2}^{n}2x_ib_i\Big]^2+v_{11}^2\mathbf{E}\Big\{\sum_{i=2}^{n}2x_ib_i\sum_{i=2}^{n}2x_i\bar{\mathbf{b}}_i\Big\}$$
$$+2v_{11}v_{12}\sum_{i=2}^{n}2x_ib_i\sum_{i=2}^{n}2y_ib_i$$
$$+v_{11}v_{12}\mathbf{E}\Big\{\sum_{i=2}^{n}2y_ib_i\sum_{i=2}^{n}2x_i\bar{\mathbf{b}}_i\Big\}$$
$$+v_{11}v_{12}\mathbf{E}\Big\{\sum_{i=2}^{n}2x_i\bar{\mathbf{b}}_i\sum_{i=2}^{n}2y_i\bar{\mathbf{b}}_i\Big\}$$
$$+v_{12}^2\Big[\sum_{i=2}^{n}2y_ib_i\Big]^2+v_{12}^2\mathbf{E}\Big\{\sum_{i=2}^{n}2y_ib_i\sum_{i=2}^{n}2y_i\bar{\mathbf{b}}_i\Big\}$$

After solving the $p2_2$, we will have

$$p2_2+p2_1=p2$$

Finally, putting the result of $p1, p2$ and $p3$ in Eq.1, the compact equation of it is obtained as shown in the Eq.2 below.

$$MSE=\begin{bmatrix}v_{11}^2+v_{21}^2\\ v_{12}^2+v_{22}^2\\ 2v_{11}v_{12}+2v_{21}v_{22}\end{bmatrix}^T\begin{bmatrix}\mathbf{E}\Big\{\big[\sum_{i=2}^{n}2x_i\bar{\mathbf{b}}_i\big]^2\Big\}\\ \mathbf{E}\Big\{\big[\sum_{i=2}^{n}2y_i\bar{\mathbf{b}}_i\big]^2\Big\}\\ \mathbf{E}\Big\{\sum_{i=2}^{n}2x_i\bar{\mathbf{b}}_i\sum_{i=2}^{n}2y_i\bar{\mathbf{b}}_i\Big\}\end{bmatrix} \tag{2}$$

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