Range Free Localization in Wireless Sensor Networks for Homogeneous and Non-Homogeneous Environment

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***Abstract*— Localization is one of the most important research subjects in terms of the wireless sensor networks (WSNs), because most of the information measured and distributed by the sensors are useful when sensors locations are well known. In this paper, a range free localization algorithm for sensor positioning is proposed. It is based on sensor distributed network model, coverage radius, hop count between each sensor and anchor, and improvement in the minimum mean square error, which computes coefficients for distance estimation between sensors and anchors. In the proposed method, the best coefficient for each hop count is computed with offline processing and Monte Carlo method. Then, these coefficients are stored in each sensor database and they are used for localization in the practical environment. Unlike some existent positioning methods, in this algorithm, it is not required to compute distance estimation coefficient by sensors. In the proposed method, it is assumed that all sensors use the omnidirectional antenna for their usual information transmission. High precision in geographical coordinate determining, less traffic load, and especially good performance in the homogeneous and non-homogeneous environment are the most important features of this algorithm. Simulation results show that the proposed algorithm has a good position determination and reduced traffic load for WSNs, as compared with some existent positioning schemes. Indeed, the proposed method improves localization precision and reduces traffic load simultaneously.**

***Index Terms*— Localization, wireless sensor networks, anchors, sensors, homogeneous, non-homogeneous.**

I. Introduction

Wireless sensor networks (WSN) have been introduced as an important tool for different applications such as searching and rescuing, targets tracking and intelligent environment creating due to their reliability, precision, profitability and ease of expansion [1]. A wireless sensor network is composed of a set of small, inexpensive, and low-power sensors, in which no especial infrastructures are needed and the sensors are required to receive the data, process them and finally transmit the information to the basis station directly or through multi hop [2]. The wireless sensor networks are highly dependent on their surrounding physical environment. To know their location is an innate feature of these networks and indeed their received data is only important in case the location of measurement is determined, and hence in many applications, it is essential that the sensors know their location [3]–[5]. Unfortunately, all sensors cannot be equipped with global positioning system (GPS) due the costs of the equipment to compute its location. The research studies conducted on the sensor localization can generally be divided into the range-based and range-free algorithms [6]. Common range-based localization methods are such as the received signal strength (RSS) [7] (which is based on measuring the received signal strength by each sensor and requires the knowledge of the transmitter strength and path losses model), time of arrival (TOA) [8] (which is based on estimation the time of arrival signal and synchronization between transmitter and receiver), time difference of arrival (TDOA) [9] and angle of arrival (AOA) [10] (which is based on the estimation of the data arrival angle by all sensors). These types of localization methods provide a reasonably high level of accuracy but they are not cost-effective. For example, one of the requirements for the localization based on the AOA method is the capability for estimation of the signal arrival angle by all the sensors. Consequently, each sensor determines its position based on the information of the transmitted signal arrival angle by three anchors. In a wireless sensor network, anchors (i.e., special sensors with known positions) are generally arranged in the form of a regular tile across the network so as to help in estimating sensors' positions. As shown in Fig. 1, sensor S with unknown location receives the signals from the anchors A, B, and C with known locations. Through the estimation of the received signal's angle of arrival from each of the anchors, then sensor S calculates its own location. On the contrary, the proposed methods in range-free part are inexpensive compared to the range-based techniques [11]. The most common methods in the range-free localization algorithm

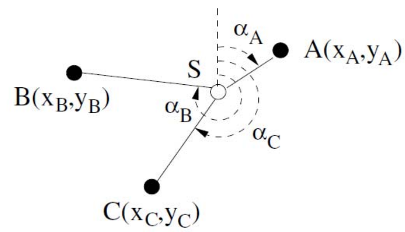

Fig. 1. The calculation of the angle of arrival for three anchor sensors A, B, and C using sensor S with unknown location [4].

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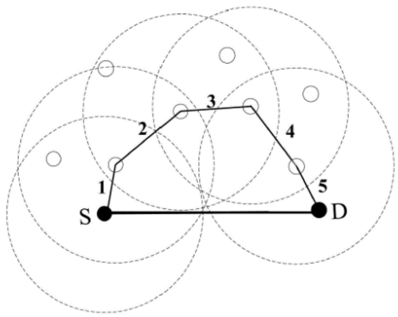

Fig. 2. Sparse array in the wireless sensor network [2].

include RAW [12], distance vector hop (DV-Hop) [13], Least Square Distance Vector Hop (LSDV-Hop) [14], Multi-hop Distance Unbiased Estimation (MDUE) [15], and localization algorithm using expected hop progress (LAEP) [2]. Estimation of the distances in such techniques is usually based on measuring the number of hops between any pair of the sensors and distance estimation through numerical or statistical methods using the information concerning the number of connections for each sensor [16]. As an example, in RAW method, the distance between the source and the destination is estimated in terms of the equation $d = h * r_0$, which h is the hop count between the source and destination nodes and r_0 shows the coverage radius of the sensors (In WSN topology, anchors are source nodes and other sensors with unknown location are destination nodes). However, if the sensors are sparsely deployed as shown in Fig. 2, RAW is prone to introduce substantial inaccuracy in distance prediction. This is due to the fact that the node density in a sparsely deployed WSN is not adequate to construct a straight and shortest multi-hop path between sensors. In this case, for any intermediate sensor along the path, the probability that the next forwarding sensor is located close to the boundary of its transmission range is extremely low. Besides, the DV-Hop method [13], due to its ruling relations, demonstrates a proper performance in the networks over which sensors distribution is thoroughly Homogeneous. However, in the non-homogeneous environment, DV-Hop shows a lot of estimation errors. In this method, the distance between the source and the destination is estimated in terms of the equation $d_i = h * HopSize_i$, where $HopSize_i$ denoted by the flowing equation:

$$HopSize_i = \frac{\sum\limits_{i \neq j} \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2}}{\sum\limits_{i \neq j} h_{ij}} \tag{1}$$

Where (x_i, y_i) and (x_j, y_j) are i's and j's anchors coordinate respectively and h_{ij} is the minimum hop counts between them. In LSDV-Hop method, $HopSize_i$coefficient can be given by

$$HopSize_i = \frac{\sum\limits_{i \neq j} h_{ij} \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2}}{\sum\limits_{i \neq j} h_{ij}^2} \tag{2}$$

In MDUE method, the distance between the source and the destination is estimated in terms of the equation

$$d = \begin{cases} \frac{2}{3} R & k = 1 \\ HopSize\,(k-2) + \alpha & k > 1 \end{cases} \tag{3}$$

Where R, k and $HopSize$ are sensor communication range, hop count between sensor and anchor and average hop counts respectively. In LAEP method, distance estimation between source and destination nodes denoted by equation $d = h * E(R)$, where $E(R)$ is the expected hop progress between neighboring sensors in a WSN. The compromise between range-based and range-free methods is proposed in [17] which improve the localization precision and reduce the amount of energy consumption.

In this paper, by MMSE improvement, measuring hop counts between sensors and anchors and considering sensors coverage radius a localization method is proposed which has good performance in the Homogeneous and non-Homogeneous environment as compared to some existent positioning schemes.

In proposed algorithm, similar to range free localization methods, all sensors use the omnidirectional antenna for transmitting their usual information.

The remainder of this paper is organized as follows: Section 2 builds the network model. Section 3 analyzes the distribution of proposed algorithm. Section 4 illustrates the theoretical and simulation results and finally, this paper is concluded in Section 5.

II. Network Model

When a WSN is randomly deployed, we cannot assume any regularity in spacing or pattern of the sensors. This is due to the fact that most WSN deployments are performed through low flying airplanes or unmanned ground vehicles. The structures that can usually be considered for the anchor installation are in quadratic, triangular, and hexagonal forms [2], [3]. In our considered network, the number of sensors is N and each sensor is defined by its number (n) in such a way that $n \in \{1, 2, \ldots, N$. Furthermore, each anchor is defined by its number (l) so that $l \in \{1, 2, \ldots, L$ and $L \ll N$. Distribution of the sensors in the two-dimensional space is expressed by the Poisson model with the average of $\lambda = \frac{N}{D \times D}$ in a square with dimensions of $A = D \times D$. Besides, it has been supposed that all sensors have omnidirectional antenna [18] and similar coverage radius r_0. Therefore, if sensor n_i is in the coverage radius of sensor n_j, then sensor n_j is also within the coverage radius of sensor n_i [2] and each sensor is regarded as the center of a circle which can be in connection with the other sensors within r_0. An illustration of how the sensors are distributed in the considered network model is provided in Fig. 3(non-Homogeneous and Homogeneous). In this figure, the red points are the anchors.

III. Sensors Localization

A. Proposed Method

In this section, the main purpose is proposing a method for distance estimation between sensors and anchors with

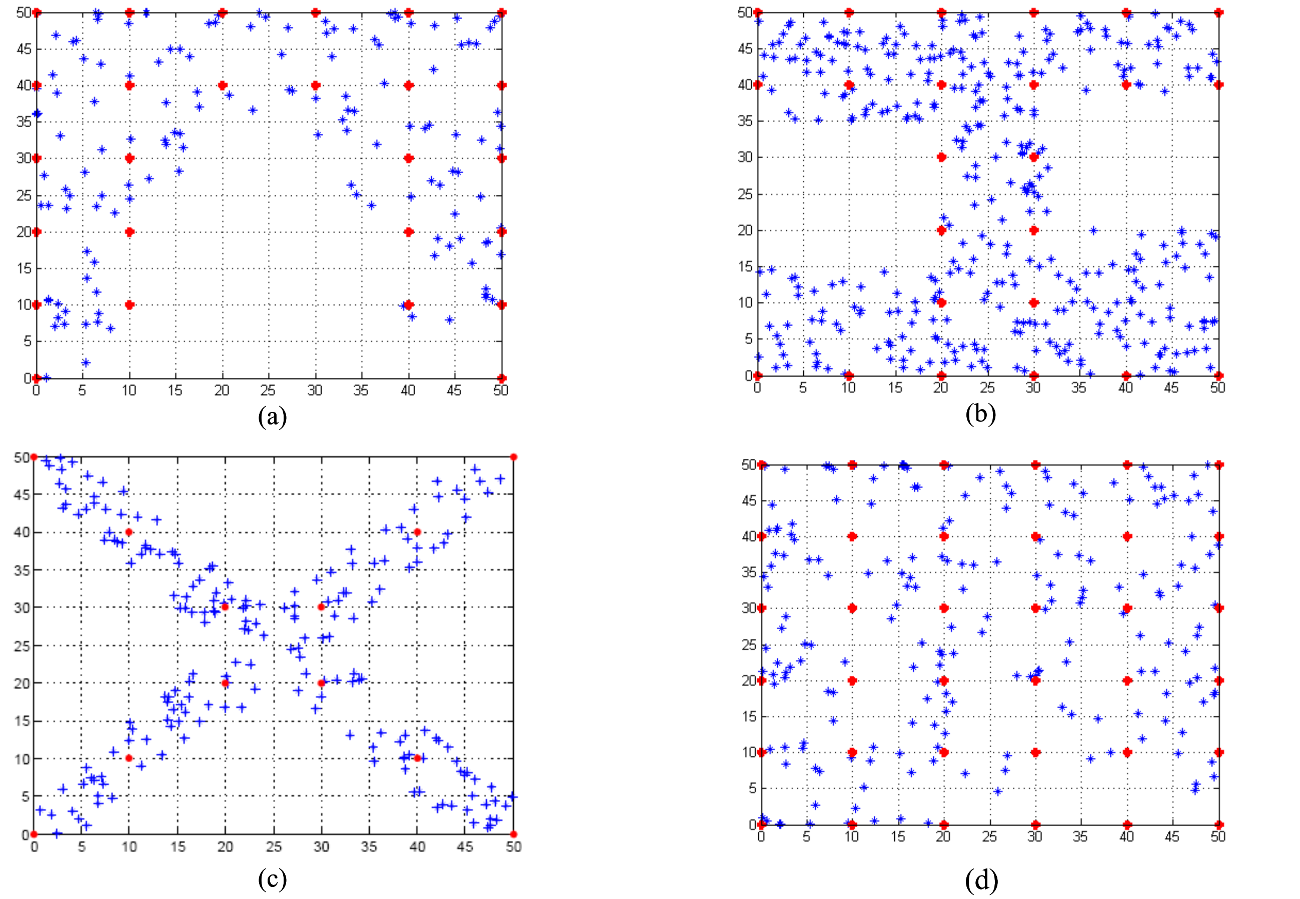

Fig. 3. Illustration of network model and sensors distribution: non-Homogeneous (a) model $\cap$, (b) model $\supset\subset$, (c) model X) and Homogeneous (d).

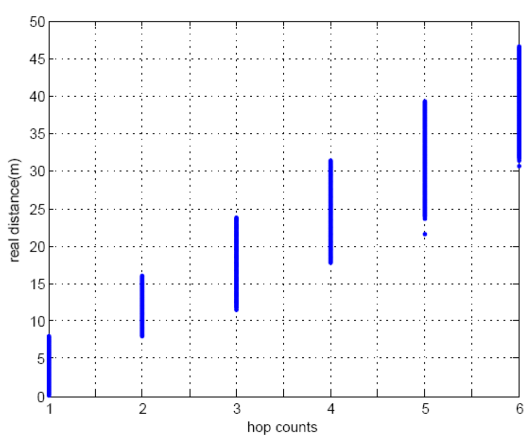

Fig. 4. Illustration of real distance based on hop counts.

minimum error. In Wireless Sensor Networks, the hop counts between sensors and anchors are related to the real distance between them. Indeed if hop counts between sensors and anchors increased, the probability of increasing real distance between sensors and anchors goes up. As shown in Fig. 4 the real distance between sensors and anchors based on hop counts between them for the same networks in Fig. 3(model (d)) is increased. Thus for each hop the real distance between sensors and anchors is variable. Then it is necessary to present an optimum coefficient for estimating the distance between sensors and anchors for each hop count. Considering above explanation, distance estimation between sensor and anchor denoted by the flowing equation:

$$\hat{d}_{n,l}^{(h)} = \beta_h^{2st} * h_{n,l} * r_0 \tag{4}$$

Where $\hat{d}_{n,l}^{(h)}$ and $h_{l,n}$ are distance estimation and minimum hop count between sensor n and anchor l respectively. β_h^{2st}, is optimum coefficient for distance estimation relative to hop counts h. In (4), $\beta_h^{2st} = \beta_h^{1st} + i_h \Delta$ and β_h^{1st} are initial coefficient of distance estimation relative to different hop counts between sensor and anchor. Also, i_h and Δ are decreasing or increasing coefficient and optimum steps for computing the optimum coefficients of distance estimation considering WSN deployment, respectively. If n's sensor distance is estimated by at least three anchors, its unique coordinate will be determined.

It should be noted that in proposed algorithm the sensors do not need to compute β_h^{1st} and β_h^{2st} coefficients in the practical environment. Before sensor deployment in practical environment, this environment is simulated by Monte Carlo method. In practical environment simulation, β_h^{1st} and β_h^{2st} coefficients are determined in steps 3 and 4.

After computing β_h^{1st} and β_h^{2st} coefficients for each hop, the optimum coefficient (β_h^{2st}) will be saved in sensors database. Then sensors are deployed in the practical environment and they use these coefficients for distance estimation between themselves and anchors.

For computing β_h^{2st}, these steps should be performed.

Step 1: Before sensors and anchors deployment in practical environments, these environments are simulated by Monte Carlo method to compute β_h^{1st} and β_h^{2st} coefficients for each hop. Some of these environments are shown in Fig 3.

Step 2: minimum hop counts between each source node (anchors) and the destination node(sensors) are computed. For measuring hop counts between sensors and anchors each anchor (e.g.,l) launches the algorithm by initiating a broadcast containing the information $I_l(ID_l, X_l, Y_l, h_{l,n})$,where ID_l signifies the identification number and (X_l, Y_l) shows the anchor l's known coordinate in a 2D space. Clearly, $h_{l,n} = 0$in the beginning.

After receiving the packet broadcasted from the anchor l, any sensor that is one-hop away from l records the anchor's information, updates its database, and then performs another broadcast to its neighbors. The new broadcast packet contains the anchor's constant information such as (ID_l, X_l, Y_l) and the updated information like $h_{l,n}$ .This process of anchor's information packet broadcasting continues until the packet arrives at any other anchor(s). In addition, each sensor keeps track of the number of anchors, whose information packet has already arrived at least once, represented by a variable Count. Initially, Count is set to 0. The event of Count beyond 3 triggers the trilateration algorithm to compute a sensor's own location. The procedure for each sensor responding to the event of information packet arriving is summarized as following: If an information packet comes, the sensor first checks the packet's origin. If it is a new anchor, it increases its local variable Count by 1, records the coordinate (ID_l, X_l, Y_l), and updates $h_{l,n}$ to its neighbors; else if the sensor has already received the information from the specific anchor, it just ignores the packet.

Step 3: After computing minimum hop counts between source and destination nodes, initially $i_h\Delta$ set to be zero and $\beta_h^{2st} = \beta_h^{1st}$. In fact for each hop count in WSN topology, a distinct initiate coefficient (β_h^{1st}) will be determined. By mean square error method we get:

$$MSE = \frac{1}{N_h}\sum_{n=1}^{N_h}(d_{n,l}^{(h)} - \beta_h^{1st} * h_{n,l} * r_0)^2 \tag{5}$$

Where $d_{n,l}^{(h)}$ is the real distance between sensor n and anchor l relative to hop count h and N_h is a total number of hop counts which is equal to h in the WSN topology. By using MMSE method we have:

$$\begin{aligned} MMSE &= \frac{\partial MSE}{\partial \beta_h^{1st}} = \frac{\partial}{\partial \beta_h^{1st}} \\ &\quad \times (\frac{1}{N_h}\sum_{n=1}^{N_h}(d_{n,l}^{(h)} - \beta_h^{1st} * h_{n,l} * r_0)^2) = 0 \rightarrow \\ \beta_h^{1st} &= \frac{\sum_{n=1}^{N_h} d_{n,l}^{(h)}}{h_{n,l} * N_h * r_0} \end{aligned} \tag{6}$$

In this step, measured coefficients (β_h^{1st}) determine final and optimum coefficient (β_h^{2st}) limits.

TABLE I

PSEUDOCODE OF ESTIMATING β_h^{2st} OPTIMUM COEFFICIENTS

Step	Comment
First	$i_h = 0, \Delta = 0.1$
Second	$i_h = i_h + 1;$ $if\left(\left\|\overline{Er_{dis}^{(h)}}(\beta_h^{1st} + i_h\Delta)\right\| < \left\|\overline{Er_{dis}^{(h)}}(\beta_h^{1st})\right\|\right)$ $i_h \rightarrow i_h++$ *else* $i_h \rightarrow i_h--$ *end*
Third	*while* *if* $i_h \rightarrow i_h--$ $if\left(\left\|\overline{Er_{dis}^{(h)}}(\beta_h^{1st} + i_h\Delta)\right\| < \left\|\overline{Er_{dis}^{(h)}}(\beta_h^{1st} + (i_h+1)\Delta)\right\|\right)$ $i_h = i_h - 1$ *else* $\beta_h^{2st} = \beta_h^{1st} + (i_h+1)\Delta$ *break* *end* *else* $if\left(\left\|\overline{Er_{dis}^{(h)}}(\beta_h^{1st} + i_h\Delta)\right\| < \left\|\overline{Er_{dis}^{(h)}}(\beta_h^{1st} + (i_h-1)\Delta)\right\|\right)$ $i_h = i_h + 1$ *else* $\beta_h^{2st} = \beta_h^{1st} + (i_h-1)\Delta$ *break* *end* *end* *end*

As it is mentioned before Step 1, β_h^{1st} and optimum coefficients β_h^{2st} are computed by practical environment simulation and Monte Carlo method. Therefor $d_{n,l}^{(h)}$ between sensor n and anchor l is known in the simulation.

Step 4: In this step, after estimating initial coefficients (β_h^{1st}), final and optimum coefficients $(\beta_h^{2st} = \beta_h^{1st} + i_h\Delta)$ will be computed. For practical environments such as Homogeneous and non-Homogeneous topology, Δ is taken to be 0.1. For determining i_h upward (i_{h++}) or downward (i_{h--}) trend, firstly, mean error distance estimation relative to hop counts h is modeled as:

$$\overline{Er_{dis}^{(h)}} = \overline{\left|d_{n,l}^{(h)} - \hat{d}_{n,l}^{(h)}\right|} \tag{7}$$

Now, if mean error distance estimation $(\overline{Er_{dis}^{(h)}})$ when $i_h = 1$ is less than $i_h = 0$, it shows that optimum coefficients (β_h^{2st}) are measured by increasing i_h $(i_h \rightarrow i_{h++})$, else it is determined by decreasing i_h $(i_h \rightarrow i_{h--})$ (first and second step of pseudocode Table I).

After determining i_h upward or downward trend, this process continues until mean distance estimation error relative to i_h reaches its minimum (Third step of Table 1). An example of measuring β_h^{2st}, when i_h is increasing, is displayed in Fig. 5.

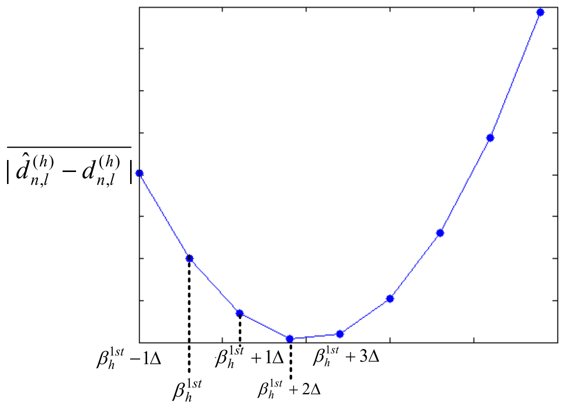

Fig. 5. A view of β_h^{2st} estimation.

As it is shown in Fig. 5, after β_h^{1st} coefficient computing, mean distance estimation error reaches minimum amount after i_h 2 units increment. Consequently, β_h^{2st} matrix form is modeled as (8) and variable H is the maximum hop count in WSN topology.

Step 5: After measuring hop counts between sensors and anchors and applying β_h^{2st} coefficients, each sensor distance is estimated by at least three anchors ($\hat{d}_{n,l}^{(h)} = \beta_h^{2st} * h_{n,l} * r_0$). Fig. 6 displays a view of sensor n localization with unknown location by three anchors l_1, l_2 and l_3. The unknown coordinate of sensor n donated by $P_n = [x_n y_n]^T$, which can be obtained by (9) [15].

$$\begin{bmatrix} \beta_1^{2st} \\ \beta_2^{2st} \\ \cdot \\ \cdot \\ \cdot \\ \beta_H^{2st} \end{bmatrix} = \cdot\frac{1}{r_0} \begin{bmatrix} \sum_{n=1}^{N_1} d_{n,l}^{(1)} & 0 & \cdot & \cdot & \cdot & 0 \\ \cdot & \sum_{n=1}^{N_2} d_{n,l}^{(2)} & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ 0 & 0 & \cdot & \cdot & \cdot & \sum_{n=1}^{N_2} d_{n,l}^{(H)} \end{bmatrix} \begin{bmatrix} \frac{1}{N_1} \\ \frac{1}{2N_2} \\ \cdot \\ \cdot \\ \cdot \\ \frac{1}{HN_H} \end{bmatrix} + \cdots \begin{bmatrix} 1 & 0 & \cdot & \cdot & \cdot & 0 \\ 0 & 1 & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & 1 & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & 1 & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & 1 & 0 \\ 0 & \cdot & \cdot & \cdot & 0 & 1 \end{bmatrix} \begin{bmatrix} i_1 \\ i_2 \\ \cdot \\ \cdot \\ \cdot \\ i_H \end{bmatrix} \Delta \quad (8)$$

$$P_n = (A^T A)^{-1} A^T b \quad (9)$$

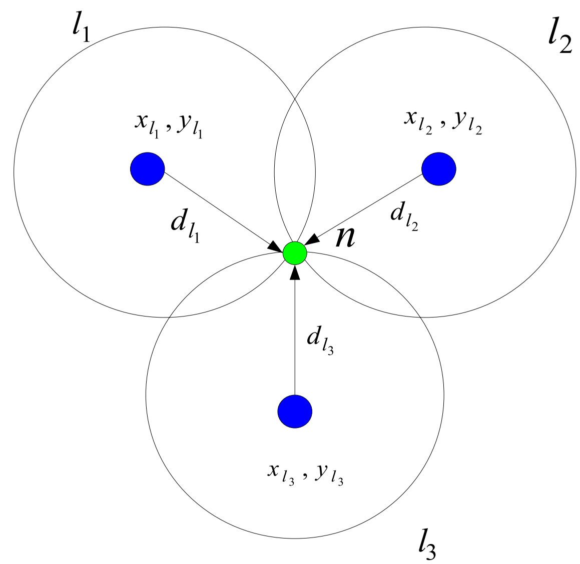

Fig. 6. A view of sensor n localization by three anchors.

Where A and b in (9) is:

$$A = 2\begin{bmatrix} x_1 - x_L & y_1 - y_L \\ x_2 - x_L & y_2 - y_L \\ \cdot & \cdot \\ \cdot & \cdot \\ \cdot & \cdot \\ x_{L-1} - x_L & y_2 - y_L \end{bmatrix}$$

$$b = \begin{bmatrix} x_1^2 - x_L^2 + y_1^2 - y_L^2 - d_{n,1}^2 + d_{n,L}^2 \\ x_2^2 - x_L^2 + y_2^2 - y_L^2 - d_{n,2}^2 + d_{n,L}^2 \\ \cdot \\ \cdot \\ \cdot \\ x_{L-1}^2 - x_L^2 + y_{L-1}^2 - y_L^2 - d_{n,L-1}^2 + d_{n,L}^2 \end{bmatrix} \quad (10)$$

Where (x_L, y_L) and $d_{n,L}$ are L's anchors coordinate and distance estimation between sensor n and anchor L respectively.

B. Error Analysis

In proposed algorithm, distance estimation error is modelled by:

$$E_r(d) = \bar{E_r}(d) + X_\sigma \quad (11)$$

Where $E_r(d)$ is the mean error in d distance from anchors and X_σ has Gaussian distribution with zero mean and variance σ^2.

In proposed method, the probability of distance estimation error being more than γ can be obtained as:

$$P_e(E_r(d) > \gamma) = Q(\frac{\gamma - \overline{E_r(d)}}{\sigma}) \quad (12)$$

Where Q function is defined as:

$$Q(z) = \frac{1}{\sqrt{2\pi}} \int_z^\infty \exp(-\frac{x^2}{2}) dx = \frac{1}{2}(1 - erf(\frac{z}{\sqrt{2}}))$$
$$Q(z) = 1 - Q(-z) \quad (13)$$

Similar to (12) the probability of distance estimation error being less than γ is:

$$P_e(E_r(d) < \gamma) = Q(\frac{\overline{E_r(d)} - \gamma}{\sigma}) \tag{14}$$

After computing β_h^{2st} coefficients, σ in (12) and (14) calculated as:

$$\sigma = \sqrt{(\frac{1}{N_h}\sum_{n=1}^{N_h}(d_{n,l}^{(h)} - \beta_h^{2st} * h * r_0)^2)} \tag{15}$$

Where N_h is a total number of hop counts which is equal to h in the WSN topology.

C. Traffic Load Comparison

Although DV-Hop, LSDV-Hop and MDUE methods determine sensors coordinates in three steps, the proposed algorithm can determine sensors location in two steps. DV-Hop, LSDV-Hop and MDUE introduce a lot of traffic load and communication delay in a WSN, due to the fact that they work in three steps. First, anchors broadcast their location information throughout the network and each sensor keeps track of the hop counts to each of the anchors. Second, any anchor estimates the average hop distance between neighboring sensors after it gets the distances to other anchors. Then, it broadcasts the corresponding average hop distance throughout the network. After the two-step broadcasting, each sensor can estimate its distance to each anchor (i.e., the product of average hop distance and corresponding hop counts), and perform the trilateration algorithm to get its estimated location in step three. As mentioned in proposed algorithm, β_h^{1st} and β_h^{2st} measuring steps are based on offline processing and Monte Carlo method. After computing β_h^{1st} and β_h^{2st} coefficients for each hop, the optimum coefficient (β_h^{2st}) will be saved in sensors database. Then sensors are deployed in the practical environment and they use these coefficients for distance estimation between themselves and anchors. In fact, sensors will not go through any process in order to obtain them (β_h^{2st}) in (4). The only process occurred for sensors localization in proposed method and practical area is calculating hop counts between source and destination nodes which are common in all methods. In DV-Hop, LSDV-Hop and MDUE methods in addition to calculating hop counts between source and destination nodes, another processing for determining hop counts coefficient mentioned in (1) and (2) is necessary. This leads to boost load traffic and energy consumption by sensors and anchors. Indeed sensor localization steps in proposed method are one step less than the others methods. RAW method and the proposed method are equal in required processing but as simulation shows, RAW accuracy is less than the proposed method.

Indeed in proposed method sensors take 2 steps for localization in the practical environment.

First: computing minimum hop counts between themselves and anchors.

Second: obtaining the unknown coordinate of sensors by (9).

It should be noted that sensors do not need computed β_h^{2st} coefficients in the practical environment. β_h^{2st} coefficients are determined before sensor deployment by means of simulation and Monte Carlo method and saved in sensors database. In another method such as DV-Hop, LSDV-Hop and MDUE sensors take 3 steps for localization in the practical environment.

First: computing minimum hop counts between themselves and anchors.

Second: computing distance estimation coefficients between themselves and anchors.

Third: obtaining the unknown coordinate of sensors by (9).

IV. Simulation Results

In order to evaluate the performance of the proposed methods, 500 sensors with 4 anchors are deployed in a square area ($A = 50 \times 50m^2$) randomly. Radius coverage is considered as $r_0 = 8m$, the average neighbor of sensors is 31, simulation area is, like Fig. 3, non-Homogeneous and Homogeneous environment and %95 of nodes are localized. Simulation is done by matlab and the area shown in Fig. 3, is simulated 100 times and distance estimation error is obtained by:

$$DEE^{i,j} = \frac{\left\| D_{estim}^{i,j} - D_{real}^{i,j} \right\|}{D_{real}^{i,j}} \tag{16}$$

In (16) $DEE^{i,j}$, $D_{estim}^{i,j}$ and $D_{real}^{i,j}$ are distance estimation error, estimated distance and real distance between sensor's i and sensor's j respectively. Table II –IX display PDF and CDF of distance estimation error in comparison with other methods in Homogeneous and non- Homogeneous environment and the best results are boldfaced for all the cases. Table II shows that the probabilities of exact distance estimation, i.e., estimation error equal to 0 , by using proposed method, DV-Hop, LSDV-Hop and MDUE algorithms show better performance than the RAW scheme and proposed method improves the accuracy of distance estimation further as compared to other methods in Homogeneous topology. It is no doubt that more accurate distance measurement leads to better position estimation.

Table IV shows that the PDF of estimation error equal to 0, by using Proposed methods, LSDV-Hop, DV-Hop, MDUE and RAW for $\cap -$ Shape topology are 0.4362, 0.2322, 0.2312, 0.2055 and 0.0066, respectively.

Table V shows that the probabilities of distance estimation deviation in the interval of ∓ 0.1 real distance for $\cap -$ Shape topology are 0.7402, 0.4171, 0.421, 0.3802 and 0.0453 by using proposed algorithm, LSDV-Hop, DV-Hop, MDUE and RAW, respectively. It is clear that proposed algorithms show better performance than other methods for $\cap -$ Shape topology. Figs. 7 and 8, illustrate PDF and CDF mean in Homogeneous and non- Homogeneous environment. Figs. 7 and 8 show that proposed method has a better performance compared with other methods in Homogeneous and non-Homogeneous topology.

Fig. 9 shows distance estimation error between sensors and anchors relative to hop counts. Comparison of distance estimation error between proposed method and others shows that the method has better performance in different hop counts. It means that distance estimation of the proposed algorithm has a high accuracy in Homogeneous and non-Homogeneous

TABLE II
COMPARISON OF THE PDF FOR HOMOGENEOUS TOPOLOGY

DEE	RAW	DV-Hop	LSDV-Hop	Proposed	MDUE
-.2	0	0.0055	0.0045	0.0190	0.0647
-.1	0	0.1725	0.1601	0.2055	0.3522
0	.0065	0.4827	0.4852	**0.5070**	0.4322
.1	0.3327	0.2598	0.2683	0.2170	0.1100
.2	0.5209	0.0539	0.0559	0.0339	0.0173

TABLE III
COMPARISON OF THE CDF FOR HOMOGENEOUS TOPOLOGY

DEE	RAW	DV-Hop	LSDV-Hop	Proposed	MDUE
0	0	0	0	**0**	0
.05	0.0065	0.4827	0.4852	**0.5070**	0.4322
.1	0.0841	0.7915	0.7931	**0.8195**	0.7345
.15	0.3391	0.9150	0.9135	**0.9295**	0.8944
.2	0.6572	0.9557	0.9549	**0.9670**	0.9546

TABLE IV
COMPARISON OF THE PDF FOR NON-HOMOGENEOUS TOPOLOGY (∩-SHAPE)

DEE	RAW	DV-Hop	LSDV-Hop	Proposed	MDUE
-.2	0	0.1113	0.0737	0.0424	0.1405
-.1	0	0.1706	0.1582	0.2308	0.1978
0	0.0066	0.2312	0.2322	**0.4362**	0.2055
.1	0.1579	0.1608	0.1544	0.2128	0.1154
.2	0.4107	0.0789	0.0742	0.0413	0.0617

TABLE V
COMPARISON OF THE CDF FOR NON-HOMOGENEOUS TOPOLOGY(∩-SHAPE)

DEE	RAW	DV-Hop	LSDV- Hop	Proposed	MDUE
0	0	0	0	**0**	0
.05	0.0066	0.2312	0.2322	**0.4362**	0.2055
.1	0.0453	0.4210	0.4171	**0.7402**	0.3802
.15	0.1646	0.5626	0.5448	**0.8798**	0.5186
.2	0.3523	0.6667	0.6274	**0.9360**	0.6298

TABLE VI
COMPARISON OF THE PDF FOR NON-HOMOGENEOUS TOPOLOGY(⊃⊂-SHAPE)

DEE	RAW	DV-Hop	LSDV-Hop	Proposed	MDUE
-.2	0	0.1364	0.1530	0.0301	0.2084
-.1	0	0.3414	0.3417	0.2309	0.3463
0	0.0065	0.2654	0.2518	**0.3711**	0.1972
.1	0.1747	0.1162	0.1118	0.2042	0.0899
.2	0.4652	0.0741	0.0721	0.0944	0.0621

environment, for different hop counts relative to other methods. All the five localization algorithms take advantage of the distance estimation to anchors for estimating sensors'

TABLE VII
COMPARISON OF THE CDF FOR NON-HOMOGENEOUS TOPOLOGY(⊃⊂ -SHAPE)

DEE	RAW	DV-Hop	LSDV- Hop	Proposed	MDUE
0	0	0	0	**0**	0
.05	0.0065	0.2654	0.2518	**0.3711**	0.1972
.1	0.0444	0.5199	0.4999	**0.6522**	0.4211
.15	0.1812	0.7229	0.7052	**0.8063**	0.6335
.2	0.4132	0.8595	0.8499	**0.8824**	0.7999

TABLE VIII
COMPARISON OF THE PDF FOR NON-HOMOGENEOUS TOPOLOGY(X-SHAPE)

DEE	RAW	DV-Hop	LSDV-Hop	Proposed	MDUE
-.2	0	0.1113	0.0737	0.0424	0.1405
-.1	0	0.1706	0.1582	0.2308	0.1978
0	0.0066	0.2312	0.2322	**0.4362**	0.2055
.1	0.1579	0.1608	0.1544	0.2128	0.1154
.2	0.4107	0.0789	0.0742	0.0413	0.0617

TABLE IX
COMPARISON OF THE CDF FOR NON-HOMOGENEOUS TOPOLOGY(X -SHAPE)

DEE	RAW	DV-Hop	LSDV- Hop	Proposed	MDUE
0	0	0	0	**0**	0
.05	0.0066	0.2312	0.2322	**0.4362**	0.2055
.1	0.0453	0.4210	0.4171	**0.7402**	0.3802
.15	0.1646	0.5626	0.5448	**0.8798**	0.5186
.2	0.3523	0.6667	0.6274	**0.9360**	0.6298

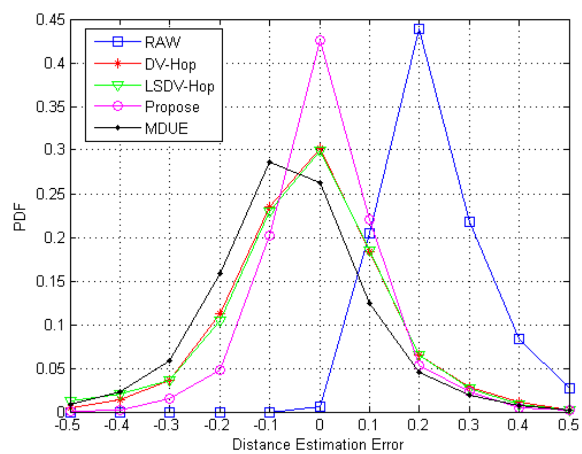

Fig. 7. Distribution of mean distance estimation error for Homogeneous and non-Homogeneous topology.

positions in a WSN. There is no doubt that more accurate distance measurement leads to better position estimation. Position estimation error (PEE) represents the position estimation deviation with respect to transmission range and can be given by

$$PEE^n = \frac{\sqrt{(x_n - \hat{x}_n)^2 + (y_n - \hat{y}_n)^2}}{r_0} \tag{17}$$

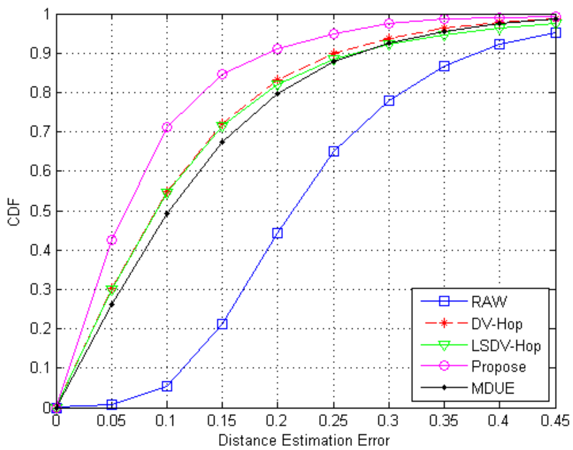

Fig. 8. Distribution of mean distance estimation error for Homogeneous and non-Homogeneous topology (continued).

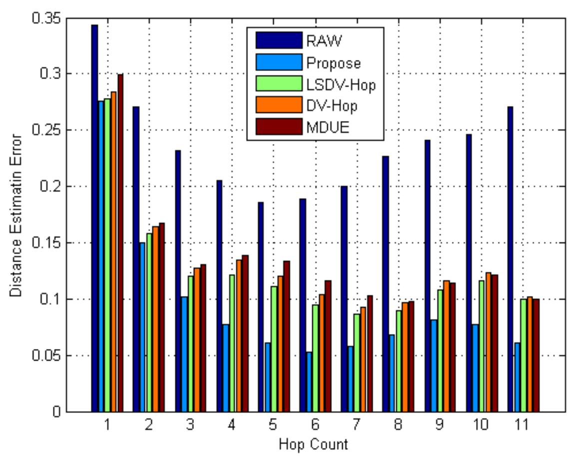

Fig. 9. Distance estimation error relative to hop counts for Homogeneous and non-Homogeneous topology (continued).

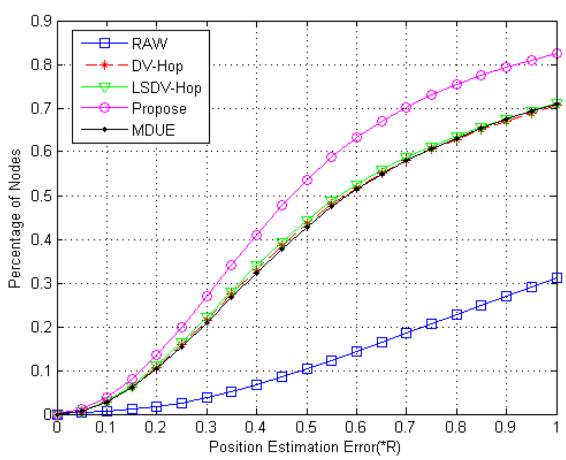

Fig. 10. Distribution of mean position error for Homogeneous and non-Homogeneous topology.

where (x_n, y_n) and $(\hat{x}_n, \hat{y}_n)$ are sensor n's real coordinates and estimated coordinates, respectively.

The errors of position estimates are normalized to r_0 (i.e., 50 percent position errors means half of the transmission range). Fig. 10 illustrates the simulation results on the mean

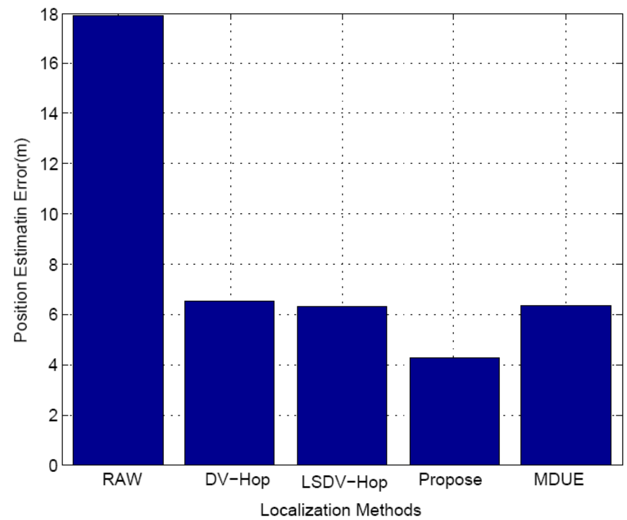

Fig. 11. Mean position error of sensors for Homogeneous and non-Homogeneous topology.

TABLE X
ESTIMATED INITIAL AND FINAL COEFFICIENT FOR NON-HOMOGENEOUS TOPOLOGY (∩ -SHAPE)

Hop count value	Initial coefficient $\beta_h^{1st} * r_0$	Final coefficient $\beta_h^{2st} * r_0$	Hop count value	Initial coefficient $\beta_h^{1st} * r_0$	Final coefficient $\beta_h^{2st} * r_0$
1	5.33	6.33	7	6.38	6.48
2	5.85	6.15	8	5.99	6.19
3	6.12	6.22	9	5.7346	6.13
4	6.39	6.49	10	5.66	6.16
5	6.48	6.48	11	5.65	6.05
6	6.46	6.46	12	4.96	5.56

position estimation accuracy in terms of position estimation error for Homogeneous and non-Homogeneous topology. It shows that by using proposed methods, over 87 percent of the sensors could estimate their positions with deviation in one transmission range from the actual locations, while only 27 percent of the sensors could be located in the same accuracy

by using RAW. (87 percent ≫ 28 percent) illustrates that proposed methods performs significantly better than RAW. In addition, using proposed algorithm, around 60 percent sensors can manage to estimate their locations within half the transmission range deviation from their real locations. Comparatively, using LSDV-Hop, DV-Hop and MDUE only around 45 percent of the sensors can achieve the same performance (60 percent > 45 percent). Figs. 11 illustrates mean position error in the Homogeneous and non- Homogeneous environments. It shows that the proposed method has a better performance in sensor positioning compared with other methods. DV-Hop, LSDV-Hop and MDUE can only provide good position estimation if the node distribution in the network, similar to the Homogeneous environment, is dense and uniform. The performance and accuracy of them deteriorate if the node distribution similar to non-Homogeneous environment is sparse or non-uniform. Considering to simulation results, estimated initial and optimum coefficients ($\beta_h^{1st}, \beta_h^{2st}$) for non-Homogeneous topology ($\cap -$ Shape) are displayed in table X.

V. Conclusion

An estimation of the physical locations for sensors is critical in WSNs. In this paper, a range-free localization has been proposed to compute the locations of sensors. In this method, distance between source and destination nodes is estimated by improving minimum mean square error, considering hop counts between source and destination nodes and sensors coverage radius. In proposed algorithm sensors do not need to compute β_h^{2st} coefficients for distance estimation in the practical environment, because they are computed before sensor deployment by means of practical environment simulation and Monte Carlo method and saved in sensor database. After that, sensors are deployed in the practical environment in order to estimate their distance from anchors by applying β_h^{2st} coefficients from their database. Simulation results show that this algorithm has a better performance in Homogeneous and non- Homogeneous environment compared with other methods.

In addition to localization precision, it reduces traffic load and necessary processing in comparison with other methods. Indeed this method improves localization precision and reduces traffic load simultaneously.

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