An Algorithm to Improve Range-Free Localization for Wireless Sensor Networks

Weaam T. EL-Gzzar, Hala B. Nafea, and Fayez W. Zaki

Abstract— The most familiar range-free positioning algorithm is the algorithm of Distance Vector-Hop. It simply uses average hop distance to reflect the distance actually, but it suffers from reduced precision because it uses only network topology, instead of distances between pair of adjacent nodes. In this work, the classic DV-Hop, RDV-Hop, and Hybrid DV-Hop algorithms are enhanced based on the differential evolution algorithm of wireless sensor network node localization. The enhanced DE algorithm has been implemented to acquire an optimal global solution that corresponds to the estimated location of the unknown node. The results of the simulation showed clearly that the new algorithms had lower average position errors and higher accuracy than the previous ones.

Index Terms—DV-Hop, DE algorithm, Hybrid DV-Hop ,localization, range-free positioning algorithm, RDV-Hop, WSN

1 Introduction

Wireless sensor networks (WSNs) consist of a community of spatially distributed and dedicated sensor nodes and are created by organizing and integrating these sensor nodes through wireless communication technologies to monitor and record environmental physical conditions and coordinate data collected at a central location. The WSNs are used in applications such as road traffic control, forest fire detection, animal habitat monitoring, precision farming, health care monitoring, disaster management, military surveillance, and environmental monitoring[1]. The analytical approach can predict the positions of sensor nodes. Such techniques are complicated and the operation gets repetitive with the network's scalability. Localization technology is a technology that supports wireless sensor networks, where sensed information becomes meaningful only with the inclusion of location parameters in most applications. There are two distinct types of sensor nodes within WSNs: an anchor or beacon node with a specified location coordinate and an unknown node to be located.

The localization algorithm's objective is to measure the unknown node locations in different ways. The global positioning system (GPS) can be used in the positioning algorithm because of its high accuracy, but there are factors that restrict its operation because it cannot be sufficient in internal and other dynamic environments [2].

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In addition to its high cost, therefore it is not practical to equip all the small sensors nodes with an identification system Global sites in WSN networks. The localization algorithm is graded into range-based and range-free localization algorithms; depending on the need to evaluate the actual distance between the various nodes in the localization process[3,4]. The Range-based localization algorithm requires extra hardware support and is therefore very costly to use in large sensor networks and it incorporates Received signal strength indicator [5], Time Difference of Arrival [6], Angle Of Arrival [7], and so on. The Range-free Localization Algorithm reduces the cost and accuracy of hardware, but can be tailored to satisfy most of the positioning needs, and therefore receives considerable attention. The Range-free Localization Algorithms include the DV-Hop algorithm, the Centroid algorithm[8], Approximate Point in Triangle (APIT) algorithm[9], and so on. DV-Hop is an algorithm that has gained considerable popularity due to its low equipment requirements and simplicity[10]. However, it suffers from reduced accuracy and has a high node energy consumption in realistic applications because it only utilizes network topology rather than distances between pairs of nodes. Therefore evolutionary algorithms are discussed in the literature for this kind of complex problem. There is a branch of the evolutionary algorithm called differential evolution algorithm. DE algorithm has been commonly utilized in a variety of areas since it has a basic structure and can easily be combined with other approaches. In order to improve the drawbacks of classic DV-hop, some articles proposed several enhancements to traditional DV-hop algorithms such as RDV-Hop[11] and Hybrid DV-Hop[12] algorithms. From simulation experiments, It is noted that these enhanced algorithms have successfully improved the precision of the localization effectively. This paper combines these improved algorithms with differential evolution algorithms to overcome the drawbacks of this algorithm and reduce the error.

The rest of this paper will be arranged according to the following. Section 2 summarizes the related work, whereas

Sections 3 and 4 consider classic DV-Hop and DE algorithms. DV-Hop Modified Techniques are outlined in Section 5 and the proposed algorithm is presented in Section 6 and the experimental results are discussed in Section 7. Finally, Section 8 offers the conclusion and future work.

2 Related work

In previous years, WSN localization has magnetized a significant number of researchers and, as a result, a number of localization algorithms have been suggested in the literature. Owing to its simplicity and high coverage, the DV-Hop location algorithm has become an economical but extremely effective location algorithm. Nevertheless, the downside is that the accuracy of the location is not very good; thus, changes in the accuracy of the location are the main issues facing this study. This work presents some related work of the DV-Hop localization algorithm. L.Gui et al. have suggested a Selected 3-Anchor algorithm at [13]. The algorithm 's idea is to use only the three best anchors for each node, rather than all the linked anchors. The choice of the best anchors is dependent on the communication between anchors and nodes. In other words, it will pick the three nearest anchors and use them for triangulation. S.Tian et al.[11] suggested that the RSSI values be used to estimate distances between their neighboring one-hop sensor and beacon nodes, otherwise, the average distance per hop used in classic DV-Hop can be used. To minimize the error occurred when the hop between the unknown node and the anchor node was 1. O.Cheikhrouhou et al. [12] used two additional steps when using the DV-Hop to locate wireless nodes and increase its accuracy. This algorithm is called a hybrid DV-hop algorithm and it gave appropriate results. V. Kumar et al.[14] calculated the sensor node location using a genetic algorithm with a differential evolution localization algorithm. The GADELA model is studied, planned, and put into effect. The algorithm shows higher accuracy and has a higher complexity in time. In terms of accuracy and time complexity, the algorithm performs well, as the population vector size is increased. In addition, the output is further improved by using the average localization function to achieve better accuracy and better time complexity. D. Han et al. [15]suggested an enhanced algorithm for the position of sensor nodes based on improved DE algorithms and DV-Hop for WSNs, namely DEIDV-Hop. Measurements and studies show that the average distance per hop of beacon nodes is improved and its benefits and effectiveness are increased. Y.Huang et al.[16] proposed to improve the precision of the weighted DV-hop algorithm by using the DE algorithm. The proposed algorithm eliminates average error in positioning and increases precision in positioning. To acquire an optimal global solution that corresponds to the estimated location of the unknown node, the differential evolution algorithm is applied, although it requires significant overhead time and energy consumption while increasing the precision of the location.

3 DV-Hop localization algorithm

DV Hop is a sort of positioning technique based on hop and distance vector information. It can even be split into three basic stages:

Stage 1: Each beacon broadcasts the location information which includes its coordinate and minimum hop count (the beginning hop count=0 for their neighbors). The minimum number of hops is stored at every beacon node and the greater number of hops from the same beacon node is ignored, the minimum number of hops is increased by one, and then modified information is forwarded to their neighbors.

Stage 2: Each beacon node uses the following equation, based on position information from the beacon node and hop count reported in the first stage, to estimate the average true distance per hop (hop size).

$$Hop\ Size_{\,i} = \frac{\sum_{i\neq j}^{N}\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}{\sum_{i\neq j}^{N} h_{\,ij}} \quad (1)$$

where (x_i, y_i) and (x_j, y_j) are the coordinates of beacon nodes i and j respectively, N is the number of beacon and h_{ij} is the hop count between these two beacons. The measured hop size information is then transmitted to the network by each beacon. The HopSize of the nearest beacon is saved by unknown nodes and sent again to the neighbor nodes.

Stage 3: The unknown node assesses the distance to every beacon node by the following equation after obtaining the average distance per hop:

$$d_{ui} = Hop\ Size_{\,i} * h_{\,ui} \quad (2)$$

where h_{ui} is the minimum hop count between unknown node u and beacon i. Assume that (x_u, y_u) is the position of the unknown node u and (x_i, y_i) is the position of the beacon node ,where i=1,2,...,m. then, the multilateration or maximum likelihood estimation approach is used to computing the coordinates of unknown nodes as [17].

$$\begin{cases} {d_1}^2 = (x_1 - x_u)^2 + (y_1 - y_u)^2 \\ {d_2}^2 = (x_2 - x_u)^2 + (y_2 - y_u)^2 \\ \vdots \\ \vdots \\ {d_m}^2 = (x_m - x_u)^2 + (y_m - y_u)^2 \end{cases} \quad (3)$$

Equation (3) can be conveyed in the form of a matrix as
A X = B, where :

$$A = \begin{bmatrix} 2(x_1 - x_m) & 2(y_1 - y_m) \\ 2(x_2 - x_m) & 2(y_2 - y_m) \\ \vdots & \vdots \\ 2(x_{m-1} - x_m) & 2(y_{m-1} - y_m) \end{bmatrix} \quad (4)$$

$$B = \begin{bmatrix} {x_1}^2 - {x_m}^2 + {y_1}^2 - {y_m}^2 + {d_m}^2 - {d_1}^2 \\ {x_2}^2 - {x_m}^2 + {y_2}^2 - {y_m}^2 + {d_m}^2 - {d_2}^2 \\ \vdots \\ {x_{m-1}}^2 - {x_m}^2 + {y_{m-1}}^2 - {y_m}^2 + {d_m}^2 - {d_{m-1}}^2 \end{bmatrix} \quad (5)$$

$$X = \begin{bmatrix} x_u \\ y_u \end{bmatrix} \quad (6)$$

The equations above are resolved by the least square method to assess the position coordinate of the unknown node u as:

$$X = (A^T.A)^{-1} A^T B \quad (7)$$

4 DIFFERENTIAL EVOLUTION ALGORITHM:

Optimization issues are omnipresent in fields of research and real-world applications such as engineering and science. Wherever resources such as space, time and cost are limited, there is a problem of optimization. Therefore, scholars and researchers require an effective and reliable optimization method to solve problems with different functions, central to their everyday activities, but it is expected at the same time that it won't be exceedingly difficult to solve a complex problem of optimization itself. Moreover, an algorithm for optimization will converge consistently to the true optimum for a variety of different problems. In addition, there should be no excessive computing tools for finding a solution. Thus, to obtain satisfactory solutions, a useful method of optimization must be easy to use, reliable, and effective. In the past decade, several evolutionary algorithms (EAs) have emerged that simulate the action and behavior of biologic organisms primarily inspired by Darwin's theory of evolution and its natural selection mechanism. In the1960s, the scientific research of EAs was started. Several researchers developed many conventional evolutionary algorithms independently, namely Genetic Algorithms [18,19], Evolutionary Programming [20], Evolutionary Strategies [21], Differential Evolution (DE) [22, 23], and Swarm Intelligence (SI) [22].

DE represents a stochastic optimization algorithm based on populations used for several variations of the DE algorithm in various practical engineering problems. In general, four basic steps [17] are in the DE algorithm, which are:

1) Initialize the population:

The initial population of the t^{th} generation $x_i^t = [x_{i,1}^t, x_{i,2}^t, \dots x_{i,D}^t]$ It is generated spontaneously randomly by normal or uniform distribution. Where the parameter variable bounded by $x_j^{(L)} < x_j < x_j^{(U)}$. The initial value of target vector (vector of current generation) is derived from equation (8).

$$x_{i,j}^0 = x_j^{(L)} + \left(x_j^{(U)} - x_j^{(L)}\right) * rand[0,1] \quad (8)$$

Where: $i = 1,2,3, \dots NP$, $j = 1,2,3, \dots D$, NP: population size, D: diminsion of the proplem ,
rand[0,1]: random numbers generated between 0 and 1, and $x_j^{(L)}, x_j^{(U)}$: is lower and upper limite of j^{th} vector component. DE enters a loop of evolutionary operations after initialization: mutation, crossover and selection.

2) Mutation operation

At each generation t ,this operation creates mutation vector v_i^{t+1} based on the current population x_i^t . The mutation vector is generated by randomly selecting 3 individual x_{r1}^t, x_{r2}^t, and x_{r3}^t from the current population. The vector differential $(x_{r2}^t - x_{r3}^t)$ is used to generate individual mutant vectors as:

$$v_i^{t+1} = x_{r1}^t + F(x_{r2}^t - x_{r3}^t) \quad (9)$$

Where: $r1, r2, r3 \in \{1,2,3, \dots NP\}$and $r1 \neq r2 \neq r3 \neq i$, F: scaling factor $F \in [0,2]$.

3) Crossover operation:

There are two types of crossover operations commonly used for DE: Binomial(uniform) and Exponential crossover [25]. After mutation, the final trial vector $u_i^{t+1} = [u_{i,1}^{t+1}, u_{i,2}^{t+1}, \dots u_{i,D}^{t+1}]$ is generated using a binomial crossover operation by crossing the target individuals $x_{i,j}^t$ and variant individual $v_{i,j}^{t+1}$. The crossover procedure is indicated in equation (10)as:

$$u_{i,j}^{t+1} = \begin{cases} v_{i,j}^{t+1}, & if\ r_j \leq P_C\ or\ j = \delta \\ x_{i,j}^t, & otherwise \end{cases} \quad (10)$$

Where, δ is randomly selected variable locaion $\delta \in \{1,2,3, \dots, D\}$,P_C is the crossover probability, and r_j is j^{th} random number between[0,1].

4) Select operation

Once all the trial vector generated, we need to do a greedy selection between $x_{i,j}^t$ and u_i^{t+1} to select the better ones from the parent vector according to their fitness values f(.), then the next generation of the individual x_i^{t+1} is generated. Greedy selection is performed only after the generation of offspring by all selection. For example, if we have a minimization issue, the selection criterion is:

$$x_i^{t+1} = \begin{cases} u_i^{t+1}, & if\ f(u_i^{t+1}) < f(x_i^t) \\ x_{i,j}^t, & otherwise \end{cases} \quad (11)$$

5 DV-HOP MODIFIED TECHNIQUES

Owing to its simplicity and cheaper cost, the DV-Hop(Distance Vector Hop), has gained attention. Nonetheless, DV-Hop is suffered from reduced accuracy as it measures just the topology of the network (i.e. Amount of hops to anchors) and not the interval distance between pairs of nodes. Moreover, if the number of hops between the unknown node and the reference node equals 1, A higher error is usually accompanied by a calculated distance value between nodes. Whereas the hop count is assumed to be 1. as long as the internodal distance comes beyond the radius of communication. As illustrated in Fig. 2, N is an unknown node; the anchor nodes are B1 and B2, and the communication radius is R. Number of hops from N and B1, and N to B2, is 1. Actually the hop count doesn't represent the distance. In this scenario, the mean single-hop distance is only rational if the nodes are evenly distributed. Errors are possible when an irregular topology is present in the network. However, if two nodes have the same number of anchor nodes hops, they both assume that the same physical condition in DV-Hop is in position, which might not be the accurate position calculation.

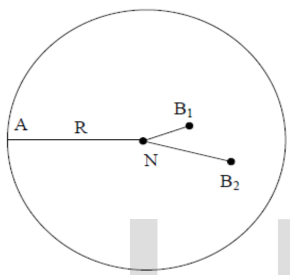


Fig.2: Hop count error

Several scholars have suggested the RDV-Hop and Hybrid DV-Hop algorithms with the technology of RSSI range to assist positioning in order to solve existing problems in the classic DV-Hop algorithm and improve the positioning accuracy. By applying signal attenuation in the transmission process, range technology of RSSI calculates the distance between two nodes; according to the following attenuation model, the distance between any adjacent nodes in the network can be achieved[26].

$$[P_L\,(d)]dB = P_{TX} - P_{RX} = [P_L(d_0)]dB + 10\eta\log(d/d_0) + X_\sigma \qquad (12)$$

Where $P_L(d)$ is the path loss if the transmission distance is d; $P_L(d_0)$ is the path loss if d_0 is the reference range of 1 meter; η is an exponent of the path loss; X_σ is a random Gauss distribution function with a mean value of 0; P_{TX} and P_{RX} are the transmitting and receiving power in dBm respectively.

5.1 RDV-HOP

The key principle of the RDV HOP algorithm [11] is to calculate the distance of the beacon nodes from their corresponding one-hop sensor nodes through the use of RSSI values. When the hop counts reach one hop, the average distance per hop in classic DV-Hop is used. We presume three anchor nodes in Fig.3: B1, B2, and B3. Node M is a node that is undefined(unknown) and has to be located. Three anchor nodes are d1, d2, and d3 with absolute distances, which are believed to be 15,30 and 30 respectively. Moreover it is assumed that each edge-length is 10. RDV-HOP can be worked as follow:

1) The average distance per-hop indicated in the equation(1), is calculated at each anchor node.
B1:(15+30)/(2+4)=7.5, B2:(15+30)/(2+4), B3=(30+30)/(4+4)=7.5

2) The RSSI packets for network transmission are generated in each anchor node and any node that receives the packet can calculate the RSSI distance from itself to the anchor by equation (12). The one-hop neighbor of the B1 and B2 anchors is node M in fig.3.

3) After receipt of RSSI packets, M calculates the distance from B1 and B2, assuming the distance is 10 and 10. The hop distance information from the anchors is less than 3. Then, using the previously defined average per-hop distance, the RDV-HOP algorithm calculates the distance from other anchors. So M figures out that 7.5 * 3 = 22.5 is the distance from B3. M will find itself using 10, 10, and 22.5 instead of 7.2, 7.5, and 22.5 by trilateration process [27].

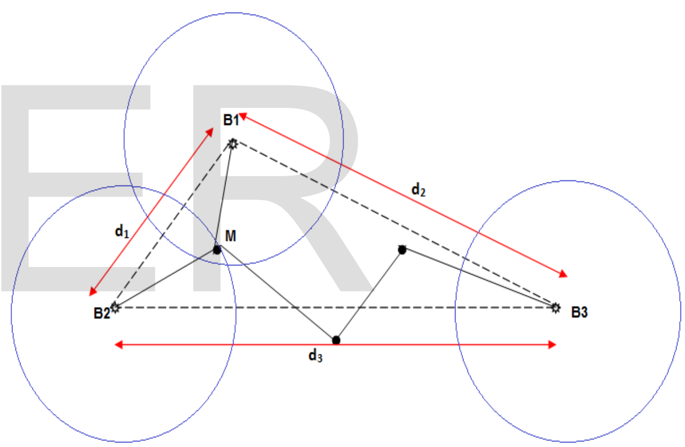


Fig.3: An example for the RDV-Hop

5.2 HYPRID DV-Hop

The basic principle of the Hybrid DV-Hop Algorithm [12] is to measure distances between each beacon and its adjacent sensor nodes with one hop as defined in the RDV-HOP algorithm using the RSSI values. Once the sensor node has been identified, it is encouraged to be used as a beacon node to locate other sensor nodes. The availability of converted beacon nodes increases the effectiveness of the rest of the sensor nodes. In particular, it is beneficial in wireless networks with lower node density. Two additional steps are used in the hybrid algorithm to localize wireless nodes from the DV-Hop algorithm.

firstly, The RSSI-based distance instead of the Hop-based distance locates the single-hop sensor node. Therefore if the node is connected with at least three separate beacon signals in direct contact (i.e. the one-hop neighbor), then trilateration can only be used to evaluate the location of the node, based on estimated RSSI distances. The other nodes are already localized by using beacons and neighbors. Moreover, during the experiments, the nodes nearest to the beacons were observed to be more accurate than the nodes far from the beacons. Sensor nodes are proposed to be localized gradually in such a way that nodes close to beacons are localized first in order to make use of that advantage.

Secondly, To begin the localization, each beacon sends a message to its neighbors. The message mainly contains the identity of the message node, the form of the message determines the node being or not a beacon and the node coordinates which constitute the real anchor coordinates and other nodes' approximate coordinates. Each node receiving this message first evaluates its position and then transfers it to its neighbors. In this approach, we make sure the nodes nearest to the beacon nodes are located first and that the position is completed gradually. The identity and the approximate location of the nearest node will memorize at every node receiving this message. When a node includes at least 3 of the anchors and/or neighbors, Trilateration can be used to determine its position.

6 Proposed Algorithm

Classic DV-Hop, RDV-Hop, and Hybrid DV-Hop algorithms typically get the co-ordinates of unknown nodes after calculating the approximate gap (estimated distance) from an unknown node to beacon node using the LSM as shown in equation(8). Because of the major errors during the positioning process which leads to a decrease in the accuracy of the localization. Therefore, The DE algorithm is utilized to improve optimum local search solutions and the accuracy of the localization algorithm. In summary, this work proposes to improve the traditional DV-Hop, RDV-Hop, Hybrid DV-Hop algorithms previously discussed based on the differential evolution algorithm of WSN node localization. The procedure for applied strategies are as follows:

1st step: initializing population according to equation (8) to get the target vector, and set the DE algorithm parameters as illustrated in table (2). The initial location of the individual is set to the closest unknown node that agrees with the position of the beacon nodes. The unknown nodes N and the beacon nodes M are randomly deployments in a network region.

2nd step: Calculating the approximate gap between the unknown nodes N and the beacon nodes M which come from three different algorithms: Classic DV-Hop, RDV-Hop, and Hybrid DV-Hop. In the case of Classic DV-Hop, the approximate gap between the unknown node and beacon node can be founded by calculating the average actual distance per hop as shown in equation(1) above, and then bring it into equation(2). In the case of RDV-Hop, the approximate gap between the unknown nodes and the beacon can be calculated from the combination of DV-hop and RSSI algorithms, where if the number of hops between the beacons and their neighboring sensor nodes is 1, uses the RSSI values to estimate distances equation(12). Otherwise, use the average hop distance used in conventional DV-Hop. In the case of Hybrid DV-Hop, as discussed before, we can get the approximate gap between the unknown nodes and the beacon after calculating the two additional steps when using the DV-Hop algorithm.

3rd step: Calculates the fitness value of each individual by the following formulas:

$$f(t) = \mathrm{Min} \sum_{K=1}^{M} \left| \sqrt{(x_i^t - x_{BK})^2 + (y_i^t - y_{BK})^2} - d_{iK} \right| \tag{13}$$

Where,(x_i^t, y_i^t) are the coordinates of the t_{th} generation's individual, and this individual corresponds to unknown node i, (x_{BK}, y_{BK}) is Kth beacon node's coordinate, and d_{iK} is the hop distance between beacon node K and unknown node i corresponding to the population individual.

4th step: Generate three random integers between 1 and NP to determine the mutant vectors according to equation (9). The process of the DE mutation occurs on all individuals in the population.

5th step: Create the trial vector according to the uniform crossover as illustrated in equation(10). The process of DE crossover occurs on all individuals in the population.

6th step: Evaluate the fitness value of each trial vector.

7th step: After each generation of t, perform greedy selection as illustrated in equation (11), and update the population(generate the next population). The target and mutant vector fitness function is measured separately, and the individual whose fitness function value is lower is retained, meaning the positioning error is lower.

8th step: After the completion of t generation, we will be able to obtain the individual location corresponding to the optimal global minimum solution.

Table 2: DE Algorithm Parameters

Name	Description	Value
F	Scaling Factor	0.9
P_C	Crossover Probability	0.5
D	Dimension of problem	2
NP	Size of Population	20
t	Number of Generation	100
L	Low boundary constraint	0
U	High boundary constraint	100

7 Results and Discussions

In this section, simulation results for the proposed algorithms using differential evolution are considered, Then A comparison is carried out between the performance of our algorithm and traditional ones. Furthermore, We evaluated the effectiveness of all algorithms in terms of two separate output results, including position error versus radio propagation range and position error versus the sum of beacons (anchor node ratio);

System Model: A wireless sensor network composed of a set number of sensor nodes of 100 is used in our first simulation. Such nodes have been uniformly distributed over a square area of 100 * 100 m. Fig.4 illustrates the deployment of sensor nodes. Matlab was used to carry out our simulations. During these tests, the radio transmissions range, and the beacon nodes ratio varies in 35m to 45m, and (8%, 25%, 35%) respectively. The same characteristics of all nodes in the network are assumed. links between neighboring nodes are also presumed as symmetric. The parameters for the simulation are listed in Table 3.

Table 3. Simulation Setup

Parameters	Specifications
Area	100x100 square area
Sensor nodes	static
Total nodes	100
Anchor nodes ratio(beacon)	8%, 25%, 35%
Placement strategies of Anchor nodes	Random
Radio Ranges	35-45m

The performance of the proposed algorithms with DE are compared with DV-Hop, RDV-Hop, and Hybrid DV-hop algorithms. The performance of all algorithms are evaluated in terms of mean localization error with respect to beacon node ratio and nodes communication range. The localization error of unknown nodes u is given as:

$$\text{Localization Error}_u = \sqrt{(x_{est} - x_i)^2 + (y_{est} - y_i)^2} \quad (14)$$

The mean localization error is expressed as:

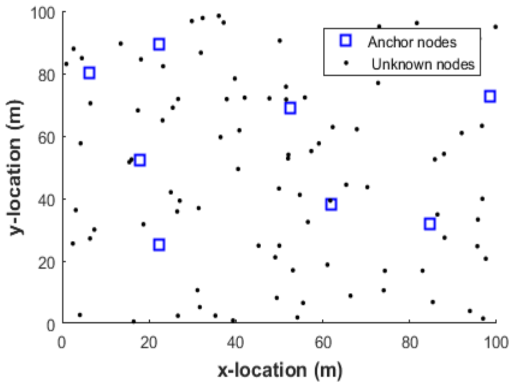
$$\text{MLE} = \frac{\sum_{i=1}^{M} \sqrt{(x_{est} - x_i)^2 + (y_{est} - y_i)^2}}{M} \quad (15)$$

Where, (x_{est}, y_{est}) is the estimated coordinate of unknown node i, (x_i, y_i) is the actual coordinate of unknown node, M is the number of unknown nodes. Table 4 illustrates the improvements in results when using differential evolution algorithms with RDV-Hop, Hybrid-DV, and classic DV. Where the mean localization error decreases significantly in the three proposed algorithms. Fig.5 includes the comparison between the mean localization error in meters and the radio transmission range. As could be shown that from these figures, localization error decreases as the transmission range increases for Hybrid DV-hop and the proposed DE hybrid DV-Hop algorithm. It is rational because the increase in the transmission range results in a greater number of single-hop beacon nodes and the RSSI factor plays its part in improving position estimate accuracy, and we can see that the hybrid DV-hop with DE produces a lower mean location error than the hybrid DV-hop. The error of position increases with the transmission radius of classic DV-Hop and DV-Hop with DE. The truth is that even sensor nodes far from the beacons can reach and be assessed, but they are expected to have relatively high estimate errors. In other words, both the estimation rate (number of calculated nodes) and the estimation error increasing, and it can be shown that the DV-hop with DE shows a lower mean localization error than the classic DV-Hop. In each hybrid DV-Hop with DE and Hybrid DV-HOP scheme, e problem is avoided because the measurement is based on neighboring nodes rather than remote beacons. In the case of RDV-Hop with DE and RDV-Hop, when the communication radius is increasing to a certain degree, the mean localization error of the two algorithms has increased. This is because the large communication radius that makes the hop count between nodes turn to be one hop, and the estimated distance between nodes are the average hop size which will bring about a big localization error, and it can be shown that the RDV-Hop gives higher mean localization error than the RDV-hop with DE.

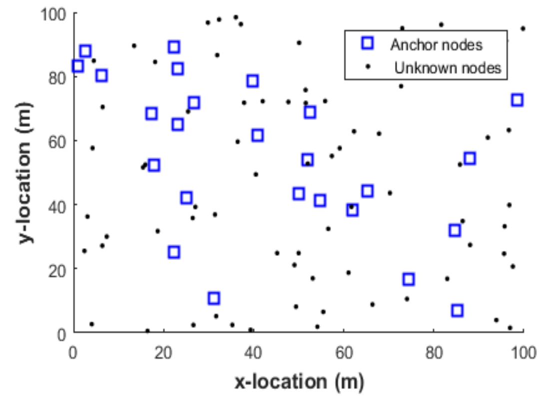
Fig.6 presents the relation between beacon nodes percentage and mean localization error for all algorithms at different values of R. In the case of Hybrid DV-Hop and Hybrid DV-Hop with DE as expected, as the number of beacon nodes in the network is increasing the accuracy in the estimated positions is improving. Where, Increased number of beacons provides greater input to the triangulation equation, resulting in greater precision.

For all the rest algorithms (RDV-Hop, RDV-Hop+DE, DV-Hop, and DV-Hop+DE), the anchor rate increases the mean localization error. This explains how additional anchors will lead to additional errors.

It can be seen in Fig.6, that the Hybrid DV-hop algorithm with DE gives the best results, where the mean localization error is less than the rest of other algorithms. The Localization error for each unknown node when the number of anchors is 8 and the communication range is 35 m are illustrated in figure 7, and we can see that the use of the differential evolution algorithm significantly improved the results.



(a)



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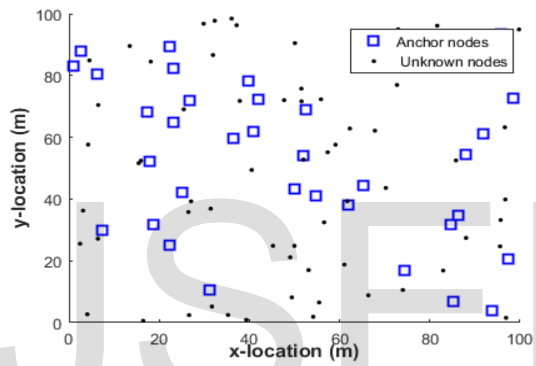
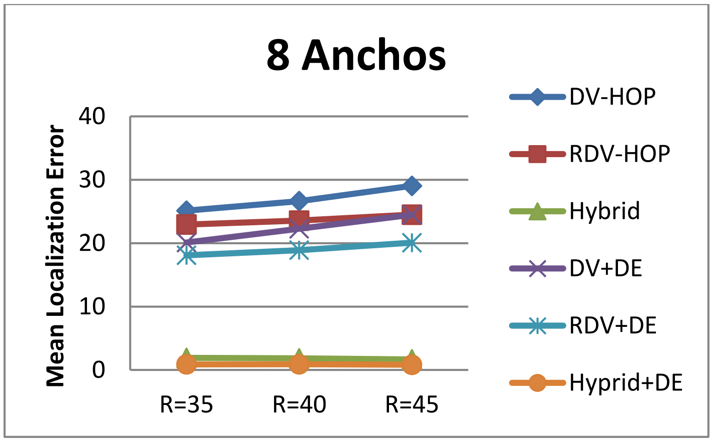


(c)

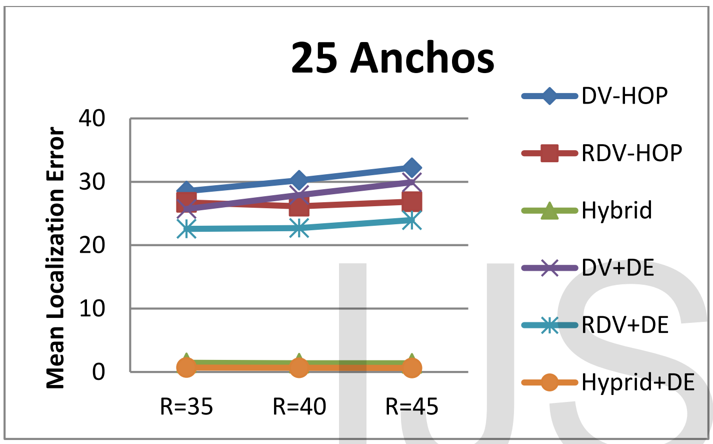
Fig.4 deployment of sensor nodes **(a)** Number of anchors=10, **(b)** Number of anchors=25, **(c)** Number of anchors=35.

TABLE 4. LOCALIZATION ERROR COMPARISON WITH DIFFERENT RANGE OF SENSOR NODES

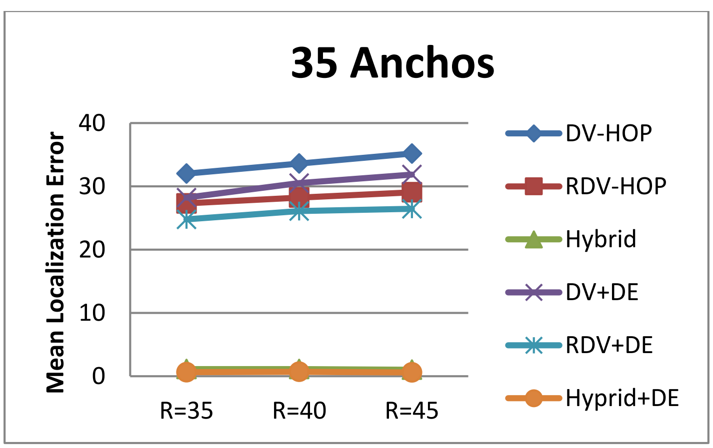
	Algorithm	**R=35**	**R=40**	**R=45**
8 Anchor	DV-HOP	25.1268	26.6313	29.0336
	RDV-HOP	22.9444	23.5521	24.4944
	HYBRID	1.9138	1.8393	1.6673
	DV+DE	20.0932	22.2753	24.4779
	RDV+DE	18.0952	18.8957	20.0772
	HYBRID+DE	0.8920	0.9051	0.8282
25Anchor	DV-HOP	28.5434	30.2354	32.2176
	RDV-HOP	26.7520	26.1438	26.8664
	HYBRID	1.4529	1.3872	1.3745
	DV+DE	25.7129	27.9114	29.9227
	RDV+DE	22.5836	22.7027	23.9568
	HYBRID+DE	0.7109	0.6752	0.6400
35 Anchor	DV-HOP	32.0187	33.6119	35.1893
	RDV-HOP	27.3114	28.2290	29.067
	HYBRID	1.1353	1.1389	1.0318
	DV+DE	28.2278	30.5241	31.8775
	RDV+DE	24.7862	26.1020	26.4569
	HYBRID+DE	0.6373	0.7007	0.6019



(a)

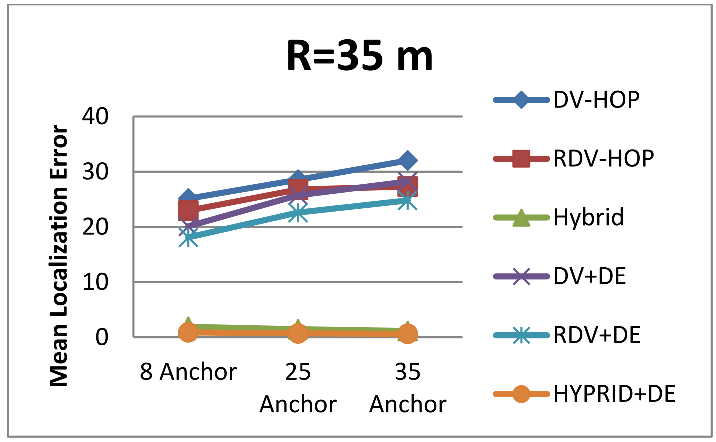


(b)

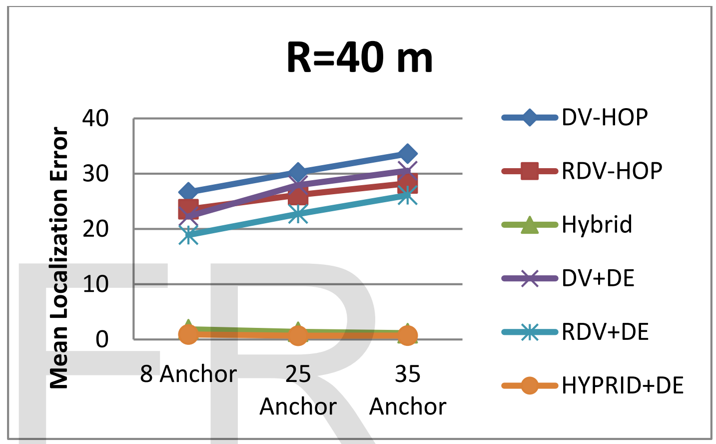


(c)

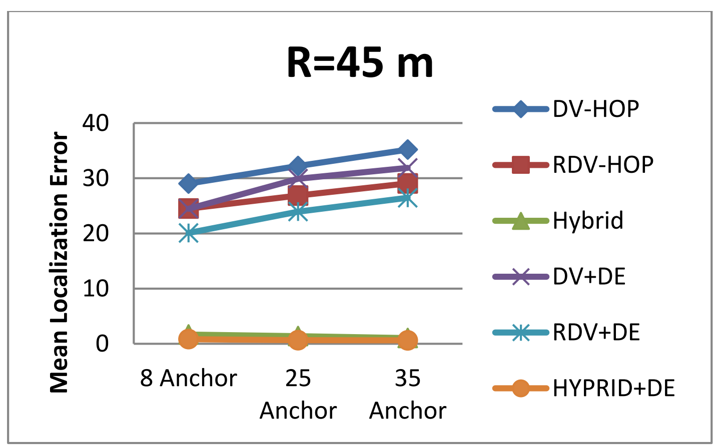
Fig.5 The effects of communication rang on the positioning error
(**a**) Number of anchors=8; (**b**) Number of anchors = 25; (**b**) Number of anchors = 35.



(a)

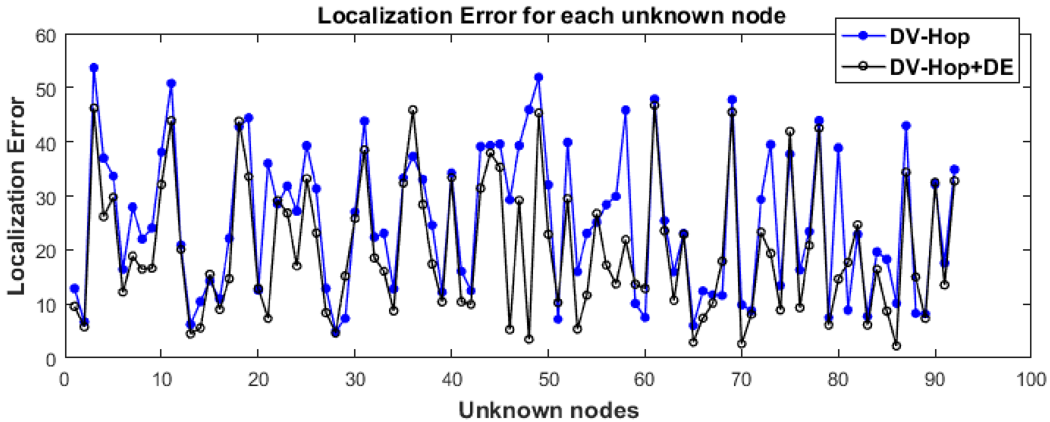


(b)

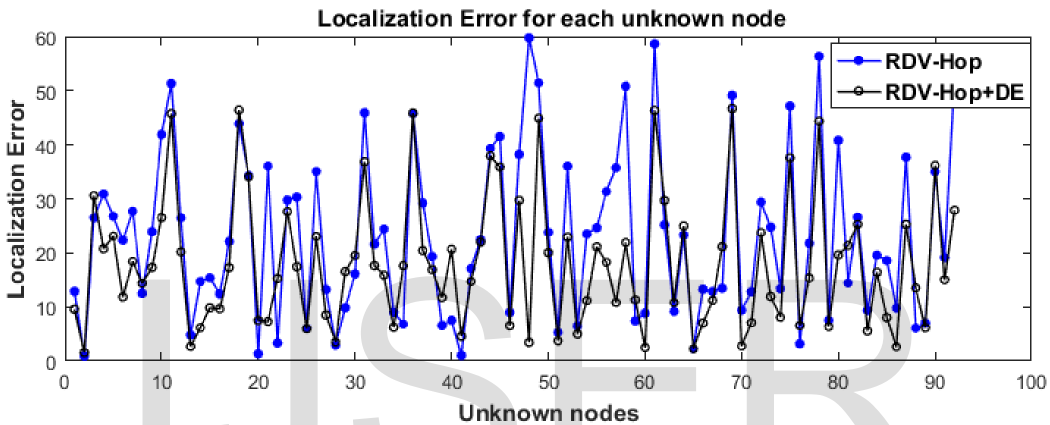


(c)

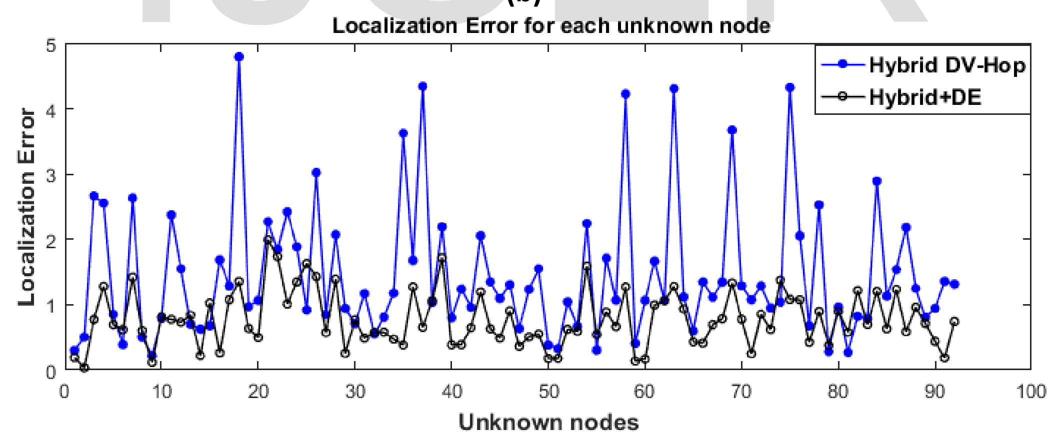
Fig.6 The effects of the number of anchor nodes on the positioning error
(**a**) communication range = 35m (**b**) communication range = 40m; (**b**) communication range = 45m.



(a)



(b)



(c)

Fig.7 Localization error for each unknown node when number of anchors=8 and R=35
(a) comparison of DV-HOP and DV+DE; (b) comparison of RDV-HOP and RDV+DE; (b) comparison of Hybrid DV-HOP and Hybrid DV+DE

8 Conclusion

To overcome the insufficient DV-Hop localization, the classic DV-Hop, RDV-Hop, and Hybrid DV-Hop algorithms are improved based on the DE algorithm of wireless sensor network node localization. The improvement used the DE algorithm in order to improve unknown node coordinates. The performance of the proposed algorithms was studied and compared with the classic DV-Hop algorithm and two recently published variants namely RDV-HOP [11] and Hybrid DV-hop algorithm [12]. The performance assessment of all algorithms showed that the proposed algorithms with differential evolution outperform their counterparts significantly. More specifically, the results are improved when using differential evolution algorithms with RDV-Hop, Hybrid-DV, and classic DV. Where the mean localization error in the three proposed algorithms decreases significantly. Nevertheless, the proposed algorithm has introduced some extra calculations as compared to the classic DV-Hop algorithm this can increase the power consumption of the node and increase the time required for the positioning. There is also a need to find a speeding up positioning and conserve time in future studies.

References

[1] G.Mao, B.Fidan, and B.Anderson," Wireless sensor network localization techniques " Computer networks, vol.51, no.10, pp. 2529–2553, 2007

[2] K. Romer and F. Mattern, "The design space of wireless sensor networks," *IEEE Wireless Communications*, vol. 11, no. 6, pp. 54-61, Dec. 2004.

[3] P.Xie, K.You, S.Song, and C.Wu, " Distributed Range-free Localization via Hierarchical Nonconvex Constrained Optimization " Signal Process, vol.164, pp. 136–145, 2019

[4] J. Bachrach,R. Nagpal, M. Salib, and H. Shrobe, " Experimental results for and theoretical analysis of a self-organizing global coordinate system for ad hoc sensor networks " Telecommunication Systems, vol.26, no.2-4, pp. 213–233, 2014.

[5] L. ZhongPeng and L.Juan "Bayesian Optimization RSSI and Indoor location Algorithm of Iterative Least Square," International Journal of Smart Home ,vol.9, no. 6 ,pp.31-42, 2015.

[6] X.Qu and L. Xie., "An efficient convex constrained weighted least squares source localization algorithm based on TDOA measurements," Signal Processing ,vol.119 ,pp.142-152,2016.

[7] W. Zhang, Q. Yin, H. Chen, F. Gao, and N. Ansari, "Distributed Angle Estimation for Localization in Wireless Sensor Networks," IEEE Transactions on Wireless Communications, vol. 12, no. 2, pp. 527-537, 2013.

[8] A. Ademuwagun and V. Fabio, "Reach centroid localization algorithm." Wireless Sensor Network , vol.9, no. 02 ,pp.87-101,2017.

[9] R. Kaur and J.Malhotra. "Comparitive analysis of DV-hop and APIT localization techniques in WSN." International Journal of Future Generation Communication and Networking, vol. 9, no. 8 ,pp.327-344, 2016.

[10] Y. Zhang, W. Xiong, D.Han, W.Chen, and J.Wang "Routing algorithm with uneven clustering for energy heterogeneous wireless sensor networks." Journal of Sensors, vol. 2016, no.9, 2016.

[11] S. Tian, X. Zhang, P. Liu, P. Sun and X. Wang, "A RSSI-Based DV-Hop Algorithm for Wireless Sensor Networks," 2007 International Conference on Wireless Communications, Networking and Mobile Computing, pp. 2555-2558, 2007.

[12] O.Cheikhrouhou, G.Bhatti, and R. Alroobaea. "A hybrid DV-hop algorithm using RSSI for localization in large-scale wireless sensor networks." Sensors , vol.18, no. 5 ,pp.1469, 2018.

[13] L. Gui, T.Val, A.Wei, and R.Dalce, "Improvement of range-free localization technology by a novel DV-Hop protocol in wireless sensor networks." Ad Hoc Networks,vol.24, pp.55-73,2015.

[14] P.Srideviponmalar, V. Kumar, and R. Harikrishnan. "Hybrid Genetic Algorithm–Differential Evolution Approach for Localization in WSN." In Intelligent Engineering Informatics, Springer, Singapore, pp. 263-271, 2018.

[15] D. Han, Y. Yunping, K.Ching Li, and R. Fernandes de Mello. "Enhancing the Sensor Node Localization Algorithm Based on Improved DV-Hop and DE Algorithms in Wireless Sensor Networks." Sensors ,vol.20, no. 2 , pp. 343 ,2020.

[16] Y.Huang, and L. Zhang. "Weighted DV-Hop Localization Algorithm for Wireless Sensor Network based on Differential Evolution Algorithm." In 2019 IEEE 2nd International Conference on Information and Computer Technologies (ICICT), pp. 14-18, 2019.

[17] D.Han, Y.Yu Y, K.Li, and R.de Mello," Enhancing the Sensor Node Localization Algorithm Based on Improved DV-Hop and DE Algorithms in Wireless Sensor Networks." Sensors, vol.20, no.2, pp.343,Jan 2020.

[18] D. E. Goldberg, "Genetic Algorithms in Search" Optimization and Machine Learning, Addison-Wesley, New York,1989.

[19] J. Holland, "Adaptation in Natural and Artificial Systems" The University of Michigan Press, Ann Arbor, Mich, USA, 1976.

[20] D. B. Fogel," Evolutionary Computation: Toward a New Philosophy of Machine Intelligence", IEEE Press, Piscataway, NJ, USA, 1995.

[21] H. Beyer and H. Schwefel, "Evolution strategies—a comprehensive introduction," Natural Computing, vol. 1, no. 1, pp. 3–52, 2002.

[22] R. Storn and K. Price, "Differential Evolution—A Simple and efficient adaptive scheme for global optimization over continuous spaces," International Computer Science Institute, vol.11, 1995.

[23] R. Storn and K. Price, "Differential evolution—a simple and efficient heuristic for global optimization over continuous spaces," Journal of Global Optimization, vol. 11, no. 4, pp. 341– 359, 1997.

[24] M.Ganbavale "Differential Evolution algorithm for structural optimization using Matlab" (2014).

[25] R.Tanabe, and A. Fukunaga. "Reevaluating exponential crossover in differential evolution." In International Conference on Parallel Problem Solving from Nature, pp. 201-210, 2014.

[26] X.Hao, L.Weisheng , L. Shanbin, and X.Bugong "An improved DV-Hop localization algorithm based on RSSI auxiliary ranging." In 2016 35th Chinese Control Conference (CCC), pp. 8319-8324. IEEE, 2016.

[27] E.Goldoni, A. Savioli, M. Risi, and P. Gamba. "Experimental analysis of RSSI-based indoor localization with IEEE 802.15. 4." In 2010 European Wireless Conference (EW), pp. 71-77. IEEE, 2010.