Gaussian-newton Localization Through Multilateration Algorithm for Wireless Sensor Networks

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GAUSSIAN-NEWTON LOCALIZATION THROUGH MULTILATERATION ALGORITHM FOR WIRELESS SENSOR NETWORKS

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Abstract: With the continuous prevalence of wireless sensor network (WSN) applications in the recent days, localization of sensor nodes became an important aspect in research in terms of its accuracy, communication overhead and computational complexity. Localization plays an important role in location sensitive applications like object tracking, nuclear attacks, biological attacks, fire detection, traffic monitoring systems, intruder detections, and finding survivors in post-disasters, etc. The objective of localization is to identify the coordinates of target nodes using information provided by anchor nodes. Precision improvement of the sensor node positions is a key issue for an effective data transmission between sensor nodes and save the node's energy as well as enhance the network lifetime. In this article, a cost-effective localization algorithm with minimal number of anchor nodes is proposed that uses nature inspired optimization techniques to enhance the localization accuracy compared to the state-of-the-art localization algorithms. The performance metrics considered for simulations and comparison with the existing algorithms include average localization accuracy, communication range, and the number of anchor nodes. The simulation results prove that the proposed gaussian-newton localization through multilateration algorithm (GNLMA) enhances the mean localization accuracy to 92.8% and the range measurement error is limited to 1.22meters. Depending on the communication range of sensor nodes, the average localization accuracy is achieved up to 94.4% using the proposed GNLMA.

Keywords: Wireless sensor networks, localization, localization accuracy, anchor node, range based localization.

1. INTRODUCTION

WSN is a key technology in smart city applications and the node's location is useful information. Installing GPS module at each SN to know its location is not cost-effective and sensor networks deployed in harsh environment cannot access GPS information. Therefore, "Nodes localization" is an important aspect to know the accurate location of sensor nodes in the WSN. The objective of localization is to assign the location coordinates to each SN in the sensing area using the known locations of few SNs called ANs. The performance of any localization techniques is considered in terms of computational complexity, communication overhead, localization accuracy, and energy consumption. Node mobility in WSNs poses challenge to the localization accuracy and the static localization algorithms fail to provide accurate locations of SNs. The ANs in WSNs are equipped with GPS chips but it has disadvantages in indoor applications and networks deployed in hard to reach areas. Therefore, localization algorithms that are independent of GPS information are essential in computing the locations of sensor nodes [1].

In the localization process, the selection of ANs play an important role and their optimal selection can minimize the uncertainties and enhance the localization accuracy by 10% [2]. The selection and deployment locations of ANs also play a crucial role in WSN localization to minimize interference and enhance information routing [3]. In a mission critical applications of WSNs, faster area exploration is achieved using mobile ANs who move in the sensing field in a coordinated fashion to help TNs in finding their locations. The area exploration schemes using the combination of cost-utility based frontier and max-gain schemes mitigate the delay and maximizes the accuracy in localization [4]. To minimize the energy consumption and enhance the location accuracy, the network region is divided into multiple sub-regions. In the first stage, the mobile ANs determine the TN region and at next stage, the location of TN is computed in the given region using trilateration [5].

Localization techniques in WSNs are broadly classified into self-localization and target localization as shown in figure 1. The aim of self-localization algorithms is to localize a sensing node by itself using signals that it receives from neighboring SNs. Target localization techniques aim to compute the position of a sensing node.

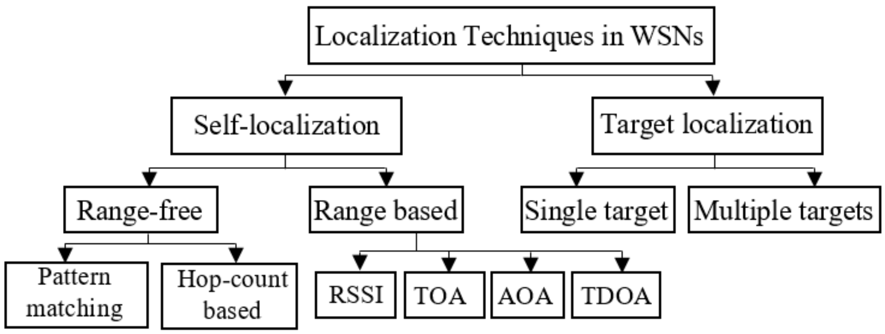

Figure 1: Classification of Localization techniques in WSNs

Depending on the kind of information needed for localization, self-localization algorithms are divided in types called “range-free” and “range-based”. Range-free algorithms use the connectivity information of SNs to localize the TNs whereas range-based algorithms use distance measurements calculated based on ToA [6], AoA [7], TDoA [8], or RSSI [9] of the received signal at SN. The first three techniques give higher localization accuracy at the cost of hardware and they are not suitable for large-scale WSNs. RSSI based localization demands for good calibration to enhance the location accuracy of mobile nodes in WSNs. GPA provides high calibration for RSSI measurements in DTN based localization. The optimal energy consumptions at SNs is equally important while finding their location coordinates. Channel-aware localization techniques can minimize the communication overhead and maximize the localization accuracy under imperfect channel conditions [10]. Range-free localization algorithms use the location information of ANs to estimate the location coordinates of TNs. The popular techniques under this category include DV-hop algorithm [11], centroid method [12], APIT [13-14], and MCB [15]. These techniques provide moderate accuracy at lower cost and power consumption. On the other side, these methods depend on environmental conditions in the network space and the spatial distribution of ANs.

The main contributions in this article include the more accuracy in measuring the distance between TNs and ANs even at low density of SNs. Computational cost-effective fitness function is defined and applied in the proposed localization algorithm. The co-planarity properties of ANs are used to minimize the location errors caused by the ANs which are in same plane. The localized TNs in the initial round of localization process are designated as assistant ANs in order to enhance the positioning coverage in the WSNs. The performance of the proposed algorithm is analyzed in terms of average localization error by considering the metrics as node density, anchor density, communication range, noisy measurements, and non-convex network areas. Intensive simulations are conducted to prove the efficiency of the proposed algorithm in terms average localization error, convergence rate, and localization success ratio. The comparative analysis has conducted under the same localization task and network deployment conditions. The rest of the article is organized as follows: section 2 briefs the nascent literature on localization techniques and methods in WSNs, section 3 describes the proposed methodology, section 4 discuss the simulation results and comparisons with the existing algorithms, and section 5 presents the conclusions and future scope of the proposed algorithm.

2. LITERATURE REVIEW

The nature inspired heuristic and metaheuristic optimization algorithms are very popular in the recent days for localization of SNs in WSNs to achieve optimal coverage, power consumption [16-18]. PSO is one of the popular meta-heuristic optimization techniques to localize the SNs in WSNs. It gives faster convergence rate and higher localization accuracy with efficient energy utilization [19]. CSA further increases the convergence rate and minimizes the communication overhead, energy consumption, localization error, and computational complexity compared to PSO algorithm. But, these algorithms are defined with a predetermined number of iterations to achieve the optimal solution. Even if the optimal solution is achieved at early number of iterations, still it causes energy loss because of predefined number of iterations. "Early stopping" method overcomes this drawback to enhance the localization efficiency and mitigates the average localization error. With suitable selection of ANs and a modified version of COA improves the accuracy of SNs location [20]. DECPSOHDV-Hop algorithm aims at ubiquitous positioning accuracy of TNs up to 90% using dynamic optimization method. Algorithms like BOA and its variants enhance the robustness, speed of localization process. The combination of heuristic algorithms such as GA, WOA improves the localization accuracy by 14.2% compared to individual algorithms [21]. The modified versions of BOA simplify the local and global search strategies thereby minimizing the computation time and mean localization error. Incorporating quantum evolution and annealing strategies into BOA enhances the global and local search capabilities in order to converge to a best optimized value. Trilateral localization used in BA improves the convergence speed and accuracy of localization by 90.35%, 75.26% compared to other heuristic algorithms in 2D and 3D WSNs. The global search capabilities of heuristic algorithms can reduce the localization error in 3D WSNs [22].

Diagonal-PSO and diagonal-centroid methods are ANs based localization algorithms where the AN traverse in a diagonal path in the given network terrain and broadcast its location coordinates. Out of these two algorithms, the PSO based heuristic approach provides more location accuracy and with minimal energy consumption. Fitness function is optimized using PSO to calculate the locations of TNs. Quantum GA optimizes the location coordinates of SNs in WSNs with minimum delays and energy consumptions. The location computations of TNs based on the degree of collinearity and GWO algorithm can reduce the number of iterations and energy consumptions. The combination of GWO-FA algorithms addresses the anisotropic properties of SNs in finding the location coordinates using a single AN and multiple virtual ANs [23]. An improved version of WOA has clustering intelligence to optimize the node localization process and enhance the positioning accuracy compared to RSSI based methods and other swarm intelligence algorithms.

AI based localization enhances the efficiency of WCL algorithm in order to achieve the higher localization accuracy. SSA is a bioinspired algorithm that performs better than other nature inspired localization algorithms such as PSO, BOA, FA, and GWO in terms of scalability, computing time, and mean localization error. Bio-inspired meta-heuristic algorithms like COA can mitigate the time taken for localizing the target node and the average localization error to 0.5m – 0.8 m. Non-linear optimization scheme called "intelligent water drops" computes range values based on RSSI. It provides global optimization by minimizing the mean squared range error between neighboring anchor nodes and increases localization accuracy compared to GA, PSO, and ACO [24].

2.1 Hop based Localization

Assigning different communication powers to the nodes in WSN establishes the accurate relation between physical distance and the hop count values. Using mobile anchor nodes, the given target node can compute its position by considering the mean distance per hop and this method mitigates the localization error. DV-hop localization algorithm based on weighted centroid in 2D WSNs provides accurate hop distance to find the optimal path. The shadowing effects of RF signal propagation in urban environment causes errors in RSSI measurements and it needs to be addressed. In hop count based localization, each TN calculates average distance to three nearest ANs which are one hop away from itself. This gives the more accurate relation between true distance and the distance per hop.

In ToA based localization, each SN computes azimuth angle, distance from its neighborhood and form a fuzzy set to compute its own coordinates. This fuzzy based localization improves localization accuracy by 33.9% compared to non-fuzzy based algorithms [25]. Average distance per hop can be considered to compute location coordinates of SNs using DV-hop algorithm in order to minimize localization errors up to 30% compared to conventional DV-hop algorithm [26]. With the given number of ANs, DEEC-GGD algorithm gives a lower localization error compared to weighted centroid, DV-hop, weighted hyperbolic, compensation coefficient algorithms [27-28]. Geographic routing is relied on a weighted centroid localization in which the positions of unknown nodes are computed using fuzzy techniques to minimize the localization error [29-30]. In order to enhance the location accuracy of DV-hop localization algorithm, an optimal subset of ANs are generated using binary PSO. Node positioning of UNs using this optimal set instead of all the ANs can minimize the computational efforts and maximize the localization accuracy [31]. RSSI based localization is one of the popular methods and it provides accurate location values using multiple scans. It demands for good calibration to enhance the location accuracy of mobile nodes in WSNs. Grey prediction scheme provides high calibration for RSSI measurements in DTN based localization. Weight assignment for the signals received at TN from the various ANs can minimize the influence of error in range measurements compared to the selection of all ANs with in the communication range. Application of a modified version of COA can further enhance the localization accuracy. With the given number of ANs, DEEC-GGD algorithm gives a lower localization error compared to weighted centroid, DV-hop, weighted hyperbolic, compensation coefficient algorithms [32].

3. METHODOLOGY

Selection of more favorable ANs and optimal number of ANs lead to the higher localization accuracy and minimize the energy consumption. In the existing optimization algorithms, once a set of optimal localization SNs are identified, the TNs in the entire network start using the same set. This causes inefficient use of ANs and leads to large errors in localization. Also, these algorithms can minimize the location deviation errors of individual TNs at the cost of higher number of iterations which will cause a huge energy consumption at SNs. Weight assignment for the signals received at TN from the various ANs can minimize the influence of error in range measurements compared to the selection of all ANs with in the communication range. In view of enhancing the localization accuracy by minimizing the localization error, we have introduced RSSI values based AN selection strategy. The ANs are SNs installed with GPS modules. The following assumptions are made for defining the proposed method and analyzing the results.

Assumptions

1. All the SNs are homogeneous in terms of hardware and communication range.
2. The communication range of ANs and TNs are equal.
3. The wireless channel in the network is anisotropic.
4. The noise and irregularities are modeled.

5. All the processes and computations are performed at the TNs in order to improve energy efficiency. When the TNs are within the communication range of ANs, they compute their own locations based on the RSSI values received from ANs. In order to localize the TNs, they need at least three RSSI values from different ANs. If the SN receives RSSI values from all the ANs, then it selects the best three values to compute its geographical location. The accurate position coordinates of TNs is achieved through the minimization of fitness function values as mentioned in equation 1.

$$F(x_m, y_m) = \frac{1}{N}\sum_{m=1}^{N}(d_{mn} - d_{mn}^1)^2 \tag{1}$$

$F(x_m, y_m)$ in equation 1 is the MSE between TN and ANs those are within the communication range of TN whose coordinates to be calculated. d_{mn} is the true distance between TN and AN whose coordinates are (x_m, y_m) and (x_n, y_n) respectively.

d_{mn}^1 is the estimated distance between TN and AN whose coordinates are (x_m, y_m) and (x_n, y_n) respectively. The estimated distance is modelled as shown in equation 2.

$$d_{mn}^1 = d_{mn} + e_{mn} \tag{2}$$

where e_{mn} is the ranging error between TN and SN whose coordinates are (x_m, y_m) and (x_n, y_n) respectively. The localization based on the fitness function presented in equation 1 involves distance measurements. RSSI values based distance measurements are efficient and simple to implement in WSNs. If there exists LOS path between AN and TN, then the free-space path loss model is used to measure the RSSI values as shown in equation 3.

$$RSSI_{d,LOS} = G_T G_R P_T (\frac{\lambda}{4\pi d})^2 \tag{3}$$

where G_T and G_R are the gains of antennas at AN and TN respectively.
P_T represents transmitting power at the AN.
'd' is the distance between AN and TN, 'λ'represents the wavelength.

In the absence of LOS path between AN and TN, the log-normal path loss model is used as shown in equation 4 which considers the multipath and shadowing effects of signal propagation in the wireless channel.

$$RSSI_{d,NLOS} = P_T - 10a\log_{10}(\frac{d}{d_0}) - PL(d_0) + X_\sigma \tag{4}$$

where $PL(d_0)$ represents the signal path loss at reference distance d_0, 'a' is the path loss exponent that lies between 2 and 4 depends on environmental conditions.
X_σ represents the gaussian noise with zero mean and standard deviation, 'σ'.
'σ^2' is proportional to the true distance d_{mn} between m^{th} TN and n^{th} AN as shown in equation 5.

$$\sigma^2 = d_{mn}^2 \times \eta^2 \tag{5}$$

where η represents the distance error factor.

In practical scenarios, larger distances between SNs in the network causes the maximum ranging and localization errors. To minimize the range measurement errors and enhance localization accuracy, an optimal AN selection strategy is proposed based on RSSI values. The proposed algorithm has mainly three steps: identification & classification of TNs, optimal ANs selection based on the class of each TN, and accurate location estimation to minimize the localization error.

3.1 Identification & Classification of TNs

At each TN, measure the RSSI values of the signals received from the ANs within its communication range using equations 3 and 4 for LOS and non-LOS paths respectively. Compute the difference between minimum and maximum RSSI values of the received signals as $RSSI_{diff}$. The $RSSI_{diff}$ value is compared with a threshold value (D_{th}) to classify the given TN as either boundary node or a non-boundary node as shown in equation 6. If the $RSSI_{diff}$ value is greater than the value D_{th}, then the corresponding TN is declared as a boundary node, otherwise it is a non-boundary sensing node.

$$\forall, TN_K = \begin{cases} \text{boundary sensing node} & RSSI_{diff} \geq D_{th} \\ \text{non-boundary sensing node} & \text{otherwise} \end{cases} \tag{6}$$

$$\text{where } D_{th} = 0.35 \times \left| RSSI_{MAX}(k) \right| \tag{7}$$

More likely, the value of RSSI is smaller if the distance between TN and AN is larger and vice versa. The value 0.35 is selected as scaling factor in equation 7 for defining the optimum threshold value.

3.2 Optimal ANs selection

The measured RSSI values of the received signals from ANs are dependent on noise due to spatial and temporal changes of the radio environment. At each TN, the received signal RSSI values from farther ANs causes more localization error. The main objective of this step is to create favorable ways to enhance the localization accuracy by mitigating the signal noise levels from the selected ANs. To achieve this objective, an optimal ANs selection strategy needs to be followed based on the given TN is a boundary node or a non-boundary node. For a boundary TN, sort out the received signal RSSI values and choose three ANs with higher RSSI values. If the TN is a non-boundary sensing node, choose all the ANs within its communication area. After conducting rigorous experiments, the proportional factor is defined as 0.8 for the boundary node to mitigate the effect of ranging errors due to farther ANs on localization accuracy.

3.3 Accurate location estimation

In order to enhance the localization accuracy further, the distances measured between each TN and the selected ANs are assigned with weights which are inversely proportional to the measured distances. In this proposed method, minimum three ANs are considered for optimal contributions in distance calculations. Different weights are assigned to different ANs and these weights are normalized using the equation 8.

$$W_n = \frac{\left[d_{mn}^1\right]^{-1}}{\sum_{n=1}^{N_{AN}} \left[d_{mn}^1\right]^{-1}} \tag{8}$$

Where W_n is the weight factor at n^{th} selected AN, d_{mn}^1 is the distance measured between m^{th} TN and n^{th} AN. N_{AN} is the number of selected ANs. From the equation 8, it is evident that the contributions of ANs are smaller when they are away from the TN.

$$F(x_m, y_m) = \frac{1}{N_{AN}} \sum_{m=1}^{N_{AN}} W_K \times (d_{mn} - d_{mn}^1)^2 \quad (9)$$

Finally, the proposed algorithm computes the location coordinates using the optimal value of the fitness function defined using the equation 9. In order to achieve minimum mean square error of localization, the value of the fitness function should be minimum. The complete steps that are followed in the proposed GNLMA algorithm are shown in the form of flowchart in figure 2.

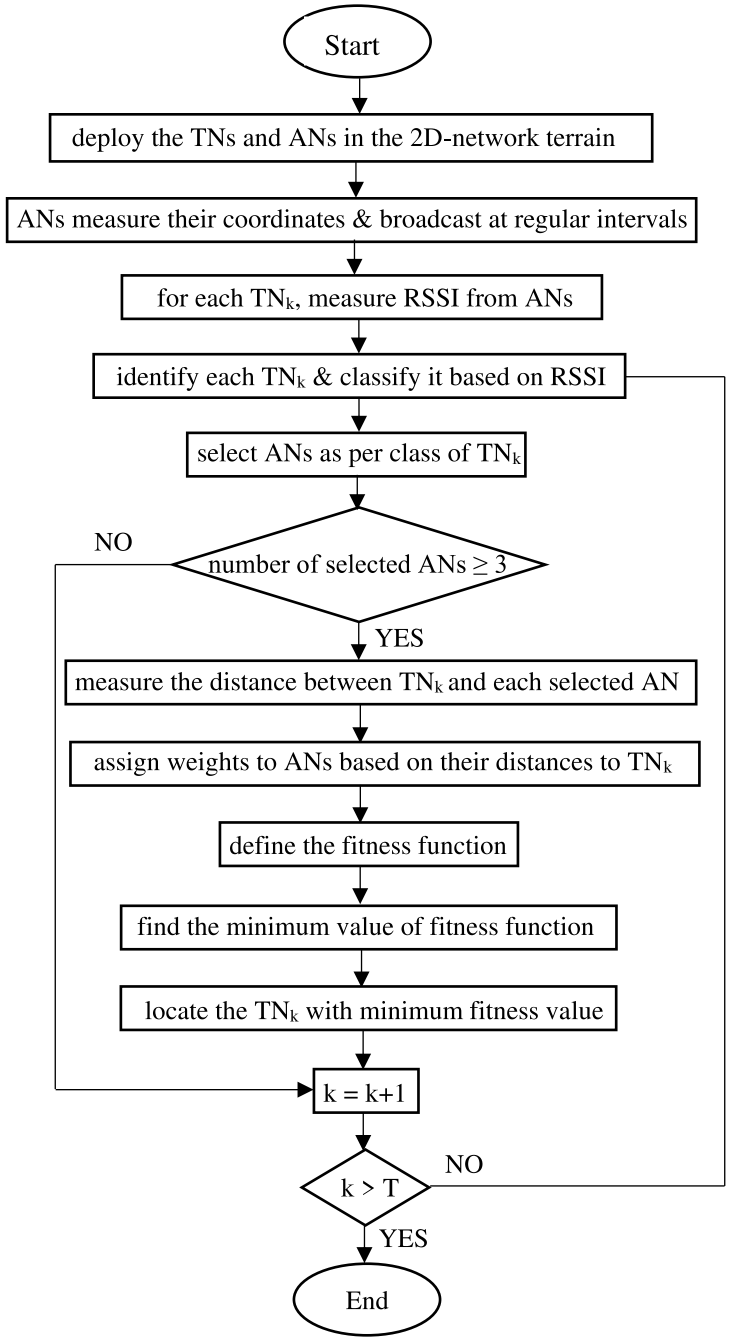

Figure 2: Flow chart of the proposed GNLMA algorithm

4. RESULTS AND DISCUSSIONS

This section presents the simulated results of the proposed GNMLA and the simulations were conducted in MATLAB 2022B tool. The number of SNs are varied from 100 to 500 and they are deployed in the geographical areas of $100\times100m^2$ to $500\times500m^2$ with random placement and the four static ANs are deployed at the corners of the network terrain. The network deployment settings and the SN parameters are presented in table 1. The performance metrics that are considered to analyze the performance of the proposed method is the average localization accuracy and mean localization error with increasing number of number of ANs and communication range. Under the ideal conditions of localization, the true location and the estimated locations are same as shown in Figure 3a. The proposed GNLMA localization method estimates the location of TNs which is very close to their true locations as shown in figure 3b to figure 3g. The simulated results (each value is averaged for thirty simulations) are also compared with the existing state-of-the-art localization algorithms [33-36].

Table 1: Simulation Parameters of the proposed GNMLA protocol

Parameter	Values
Network terrain dimensions	$100m\times100m$, $500m\times500m$
Number of sensor nodes	100 to 500
Initial energy (E_0)	0.5J
Number of Anchor Nodes	4
Node density	$0.02m^2$ and $0.03m^2$
Maximum communication range, R	50m
Free-space energy (E_{fs})	50nj/bit
Energy required to run the circuity(E_{elec})	$0.0013pj/bit/m^4$
Energy consumed by the amplifier for bit transmissions (E_{amp})	$10pj/bit/m^2$
Data Packet size	4000-bits
Maximum number of iterations	100
Number of simulations per reading	30

The average or mean localization error is computed using equation 10 as,

$$\text{The mean localization error} = \frac{\sum_{i=1}^{N}\sqrt{(x_m - x_n)^2 + (y_m - y_n)^2}}{N} \tag{10}$$

where (x_m, y_m) are the actual coordinates of the TN and (x_n, y_n) are the estimated coordinates of the TN. ‘N’ is the total number of SNs in the network.

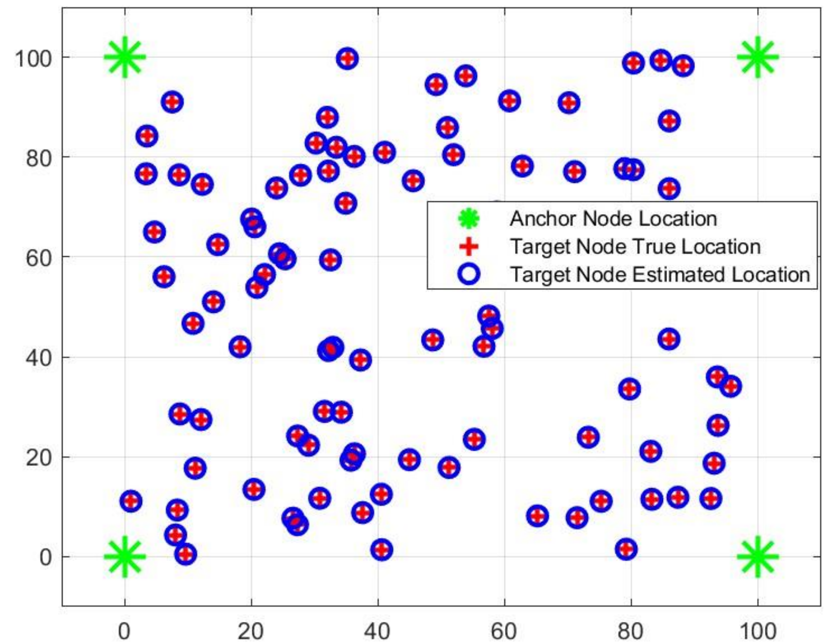

Figure 3a: Ideal case of sensor nodes location estimations in a 100 $\times$100 meter^2 network terrain

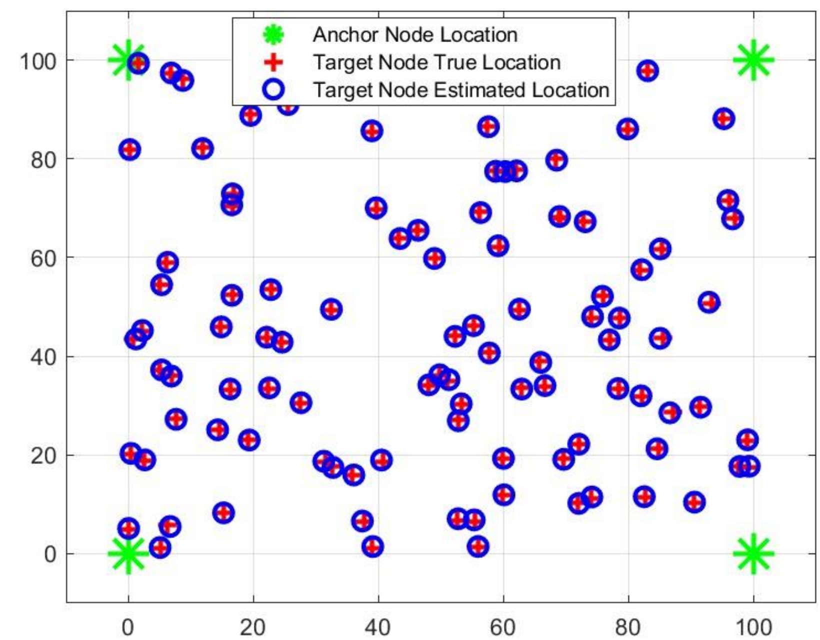

Figure 3b: Localization of 100 sensor nodes in a 100 $\times$100 meter^2 network terrain using the GNMLA method

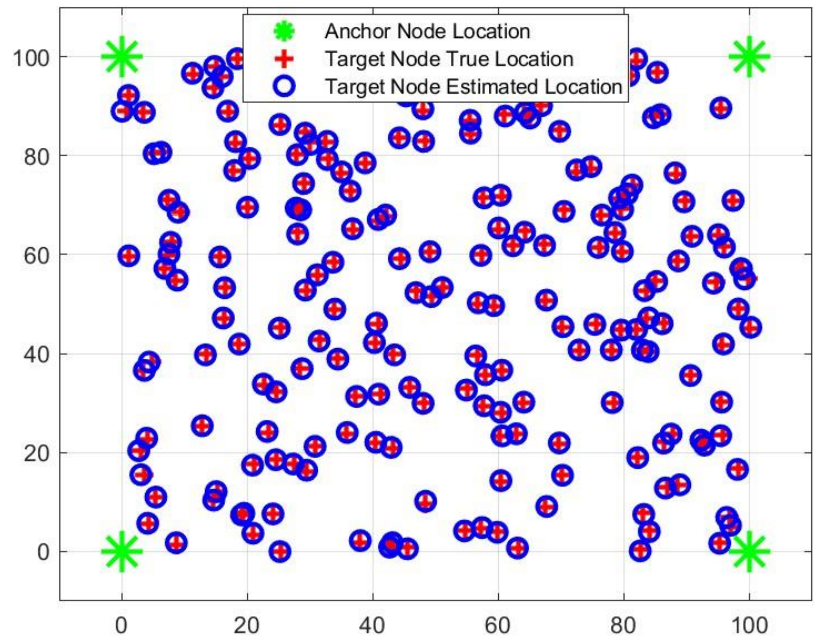

Figure 3c: Localization of 200 sensor nodes in a 100 $\times$100 meter^2 network terrain using the GNMLA method

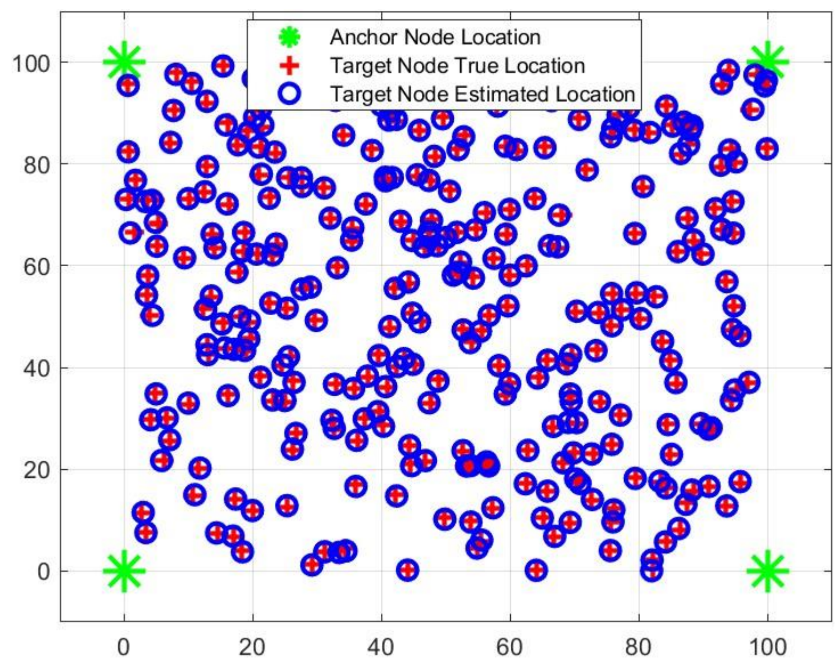

Figure 3d: Localization of 300 sensor nodes in a 100 $\times$100 meter^2 network terrain using the GNMLA method

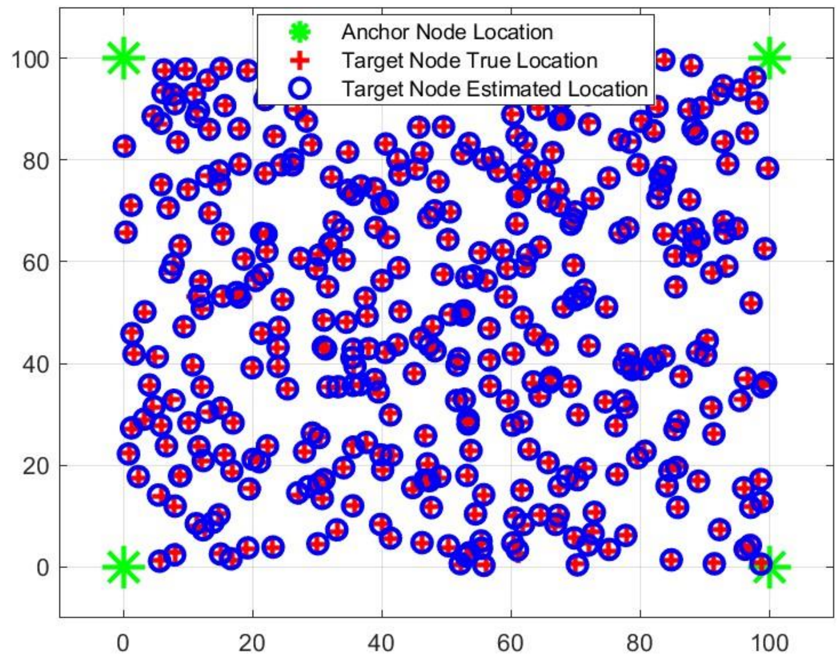

Figure 3e: Localization of 400 sensor nodes in a 100 $\times$100 meter^2 network terrain using the GNMLA method

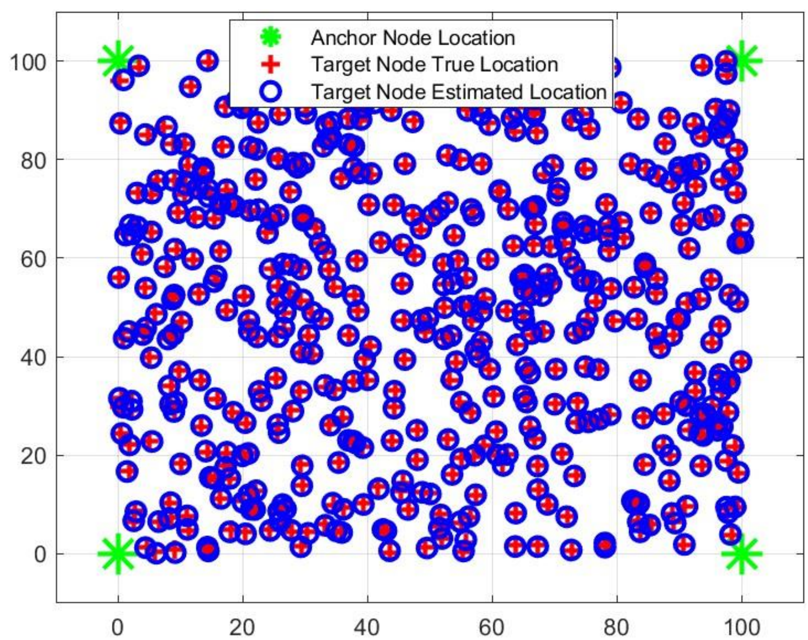

Figure 3f: Localization of 500 sensor nodes in a 100 $\times$100 meter^2 network terrain using the GNMLA method

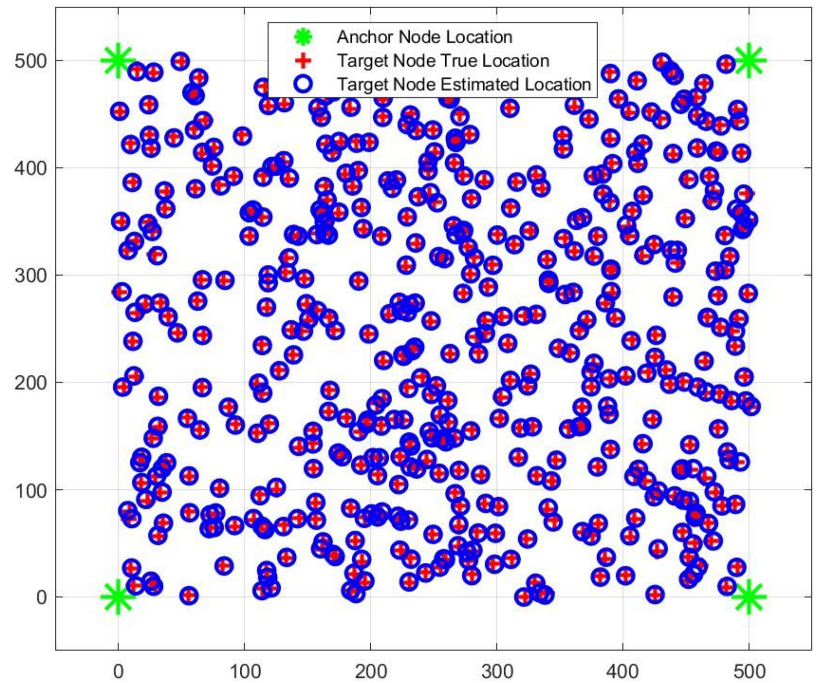

Figure 3g: Localization of 500 sensor nodes in a 500 × 500 meter^2 network terrain using the GNMLA method

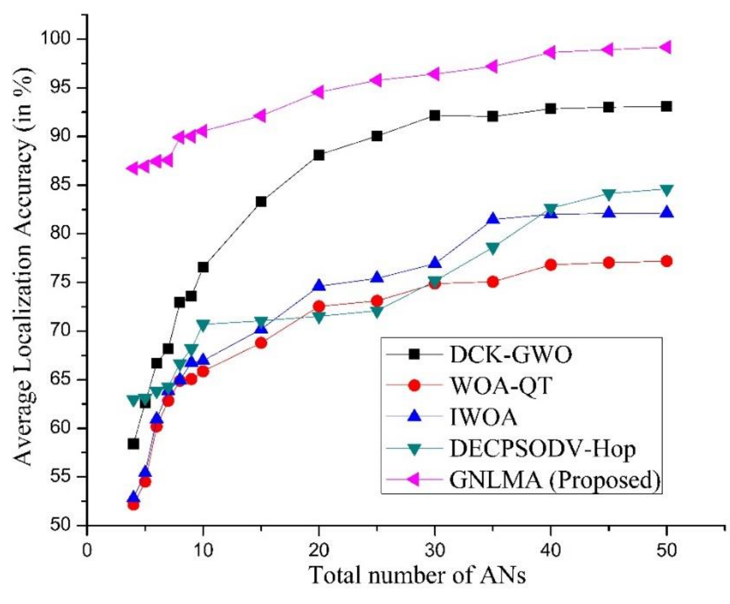

Figure 4: Average Localization Accuracy versus Total number of Anchor Nodes

In figure 4, the average localization accuracy of the proposed GNLMA algorithm is compared with the other meta-heuristic optimization based localization algorithms. It shows that that the DCK-GWO [37] algorithm is performing better than the other meta-heuristic optimization algorithms. It works based on the degree of K-value collinearity with improved GWO. This algorithm gives better localization accuracy only when the AN ratio is above 20% and also the communication range should be at least 35m. Therefore, it leads to higher GPS hardware costs and higher number of computations in the network. The DECPSOHDV-

Hop algorithm [38-39] provides stability and localization accuracy of 84.62% at the AN ratio of 50 and communication radius of 50m. WOA based localizations [40-41] are performing poor in terms of localization accuracy compared to the other algorithms. However, the proposed GNLMA algorithm is providing 86.72% of localization accuracy even with four ANs and it is further increases linearly with increasing number of ANs. In this way, the proposed algorithm is minimizing the hardware cost and computational cost in the network. The reason for achieving higher localization accuracy using the proposed algorithm is that the selection of more favorable and optimal number of ANs lead to the higher localization accuracy and minimize the energy consumption. Also, the TNs are not dependent on a particular set of ANs instead the location measurements are performed in a distributed manner and it leads to minimal number of iterations. The localization accuracy using the proposed GNLMA algorithm is enhanced by 12.56%, 22.36%, and 20.83% compared to DCK-GWO, IWOA, DECPSODV-Hop algorithms respectively as shown in Table 2.

Table 2: Average Localization Accuracy (in %) vs Number of ANs

	Number of ANs														
Protocol	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**	**Average**
DCK-GWO	58.42	62.61	66.72	68.18	72.92	73.56	76.54	83.28	88.12	90.04	92.17	92.05	92.85	93.02	93.08	80.24
IWOA	52.84	55.42	60.94	63.85	64.96	66.75	66.96	70.19	74.61	75.42	76.92	81.45	82.02	82.08	82.14	70.44
DECPSODV-Hop	62.96	63.12	63.82	64.25	66.67	68.19	70.69	71.05	71.52	72.09	75.15	78.6	82.64	84.15	84.62	71.97
GNLMA (Proposed)	86.72	86.92	87.45	87.56	89.91	90.01	90.56	92.14	94.55	95.78	96.42	97.21	98.64	98.92	99.18	92.80

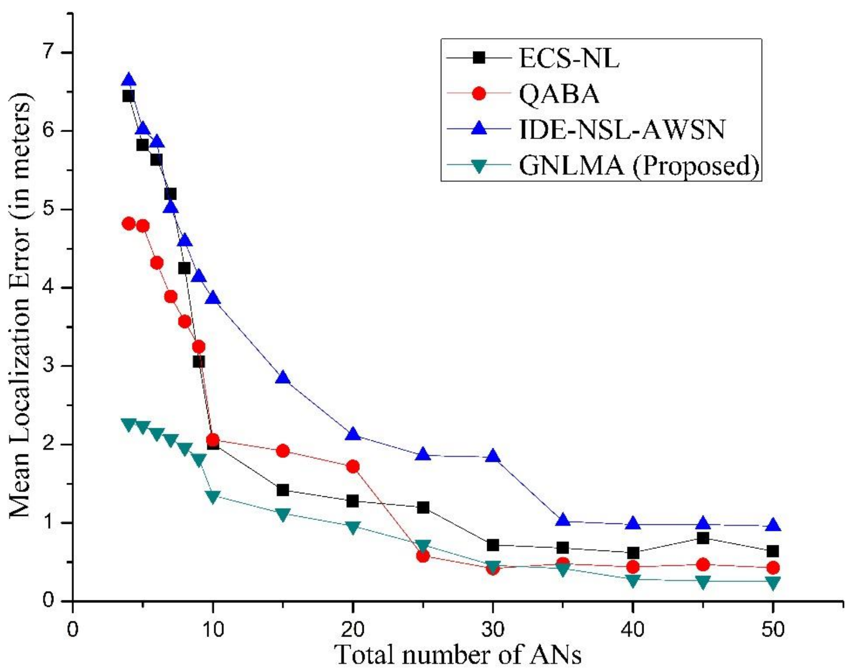

Figure 5: Mean Localization Error versus Total number of Anchor Nodes

For ease of comparison, the maximum number of iterations and population size are kept constant for ECS-NL, QABA, IDE-NSL-AWSN, and the proposed GNLMA algorithms. The average value of 30 consecutive simulations is considered for performance comparison. Bio-inspired meta-heuristic algorithms like COA can mitigate the time taken for localizing the target node and the average localization error up to 0.5m. The localization error in ECS-NL algorithm [42] is limited to 0.5m to 2m and the errors are decreased with increasing node density, but the minimum number of ANs needed are 10. This will increase the need of GPS modules and cost of the network. IDE-NSL-AWSN was proposed to enhance the distance estimation that depends on SN selection in an obstacle-aware WSNs. But, it needs at least 15m and 75m as communication range in small-scale and large-scale environments for each SN in order to have at least one connection and the average localization error is limited to 2.54m [43]. Incorporating quantum evolution and annealing strategies into BA enhances the global and local search capabilities in order to converge to a best optimized value. Trilateral localization used in BA improves the convergence speed and accuracy of localization by 90.35%, 75.26% compared to other heuristic algorithms in 2D and 3D WSNs. QABA algorithm gives higher localization accuracy when the minimum communication range is 30m and the average error is limited to 1.25m [44]. Overall, the localization error is minimum with the proposed GNLMA algorithm compared to the other algorithms considered in figure 5 especially when the number of ANs are less than 10. This feature is attractive to build cost-effective localization algorithms for WSNs. From table 3, the localization error using the existing localization algorithms is mitigated to minimum levels only after the number of ANs are increased to 10 whereas the need of ANs is limited to four using the proposed algorithm to reach the same error values. There is 117.21%, 81.48%, 166.49% improvement in localization measurements using the proposed GNLMA algorithms compared to ECS-NL, QABA, IDE-NSL-AWSN algorithms respectively.

Table 3: Mean Localization Error (in meter) vs Number of ANs

	Number of ANs														
Protocol	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**	**Average**
ECS-NL	6.45	5.82	5.64	5.2	4.25	3.06	2.01	1.42	1.28	1.2	0.72	0.68	0.62	0.81	0.64	2.65
QABA	4.82	4.79	4.32	3.89	3.57	3.25	2.06	1.92	1.72	0.58	0.42	0.48	0.44	0.47	0.43	2.21
IDE-NSL-AWSN	6.64	6.02	5.85	5.02	4.59	4.14	3.86	2.84	2.12	1.86	1.84	1.02	0.98	0.98	0.96	3.25
GNLMA (Proposed)	2.27	2.24	2.15	2.07	1.96	1.82	1.35	1.12	0.96	0.72	0.46	0.42	0.28	0.26	0.25	1.22

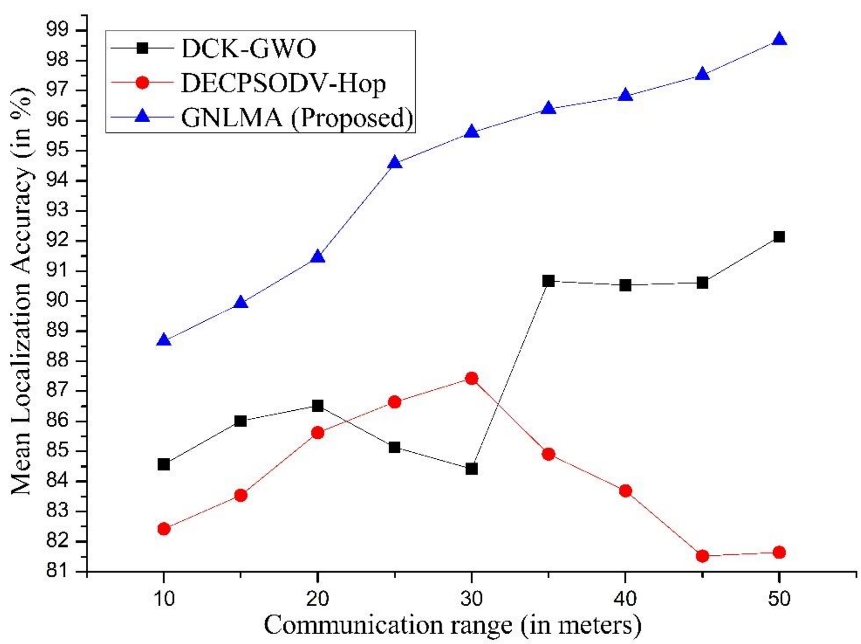

Figure 6: Mean Localization Error versus Communication range

The communication range of SNs affects the localization accuracy through the suitable ANs selection. The localization accuracy improves with the communication range as more number of ANs are participated in localization. In figure 6, as the communication range increases, the localization accuracy increases using the proposed GNLMA algorithm and it has linear relation. But, with the meta-heuristic and hop-based algorithms the average localization accuracy is less and also linear relation does not hold good between communication range and localization accuracy. From the table 4, the localization accuracy is improved by 6.55% and 10.24% in the mean localization accuracy of the proposed GNLMA algorithm compared to DCK-GWO and DECPSODV-Hop algorithms respectively.

Table 4: Communication range vs Mean Localization accuracy (in %)

Protocol	**Communication range in meters**									
	10	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**	**Average**
DCK-GWO	84.57	86.01	86.52	85.14	84.42	90.67	90.53	90.62	92.14	87.85
DECPSODV-Hop	82.42	83.54	85.62	86.64	87.43	84.91	83.69	81.52	81.64	84.16
GNLMA (Proposed)	88.67	89.92	91.45	94.58	95.61	96.39	96.82	97.52	98.68	94.40

The modified versions of BOA simplify the local and global search strategies thereby minimizing the computation time and mean localization error [45]. Considering different communication powers to the nodes in WSN establishes the accurate relation between physical distance and the hop count values. Using mobile ANs, the given TN can compute its position by considering the mean distance per hop and this method mitigates the localization error [46].

5. CONCLUSIONS AND FUTURESCOPE

The proposed GNLMA algorithm addresses localization and optimal coverage problems in WSNs in a cost-effective manner with reduced computational cost compared to other meta-heuristic as well as range-based localization algorithms. The low complexity fitness function is defined and applied in the proposed localization algorithm. This algorithm reduces the number iterations in achieving the global optimal solution even at the lower values of communication range, AN ratio, and node density. The simulation results prove that the proposed GNLMA algorithm enhances the mean localization accuracy to 92.8% and the range measurement error is limited to 1.22meters. Depending on the communication range of sensor nodes, the average localization accuracy is achieved up to 94.4% using the proposed GNLMA. From the overall results, even though the localization performance of all the algorithms are increasing with increasing number of ANs, the minimum number of ANs are reduced to four in the proposed algorithm without compromising for localization accuracy. The presence of higher ANs and SNs density lead to further enhancement of the location estimation precision. As a future work of this, the reposed algorithm is implemented in the hardware of SNs during the real-time deployment of WSNs.

GLOSSARY

2D	two dimensional
3D	three dimensional
ACO	ant colony optimization
AN	anchor node
AoA	angle of arrival
APIT	approximate point in triangulation test
BA	bat algorithm
BOA	butterfly optimization algorithm

BFO	bacterial foraging optimization
COA	cuckoo optimization algorithm
CSA	cuckoo search algorithm
DCK	degree of K-value collinearity
DECPSOHDV	differential evolution chaotic PSO Hybrid DV
DEEC	distributed energy efficient clustering
DTN	dynamic triangulation algorithm
DV	distance vector
ECS-NL	enhanced CSA for node localization
FA	firefly algorithm
FPA	flower pollination algorithm
GA	genetic algorithm
GGD	gaussian gradient distance
GNLMA	gaussian newton localization through multilateration algorithm
GPA	grey prediction algorithm
GPS	global positioning system
GTP	gorilla troop optimizer
GWO	grey wolf optimization
IDE-NSL-AWSN	improving distance estimation based on node selection in obstacle-aware WSNs
IWO	invasive weed optimization
IWOA	improved whale optimization algorithm
LOS	line of sight
MCB	Monte Carlo Localization Boxed algorithm
ML	maximum-likelihood
MSE	mean square error
PIR	pyroelectric infrared
PLD	parametric loop division
PSO	particle swarm optimization
QABA	quantum annealing bat algorithm
RF	radio frequency
RSSI	received signal strength indicator
SN	sensor node
SSA	salp swarm algorithm
TDoA	time difference of arrival
TN	target node
ToA	time of arrival
UN	unknown node
WOA	whale optimization algorithm
WSN	wireless sensor network

Declarations

Ethical Approval: Not Applicable

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