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# Modified Bat Algorithm for Localization of Wireless Sensor Network

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**Abstract** The problem of node localization in wireless sensor networks aims to assign the geographical coordinates to each device with unknown position, in the deployment area. In this paper the meta heuristic optimization algorithm known as bat algorithm is described in order to evaluate the precision of node localization problem in wireless sensor networks. Meanwhile the existing bat algorithm has also been modified by using the bacterial foraging strategies of bacterial foraging optimization algorithm. Compared with the existing bat algorithm, the proposed modified bat algorithm is shown through simulations to perform constantly better not only in increasing localization success ratios and fast convergence speed but also enhance its robustness.

**Keywords** Wireless sensor network · Localization · Bat algorithm · Modified bat algorithm

## 1 Introduction

Recent advances in radio and embedded systems have enabled the proliferation of wireless sensor networks. Wireless sensor networks (WSNs) are tremendously being used in different environments to perform various monitoring tasks such as search, rescue, disaster relief, target tracking and a number of tasks in smart environments. In many such tasks, node localization plays a key enabling role. Node localization is required to report the origin of events, assist group querying of sensors, routing and to answer questions on the

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network coverage. So, one of the fundamental challenges in wireless sensor network is node localization [1]. In a sensor network, there will be a large number of sensor nodes densely deployed at positions which may not be predetermined. In most sensor network applications, the information gathered by these micro-sensors will be meaningless unless the location from where the information is obtained is known. This makes localization capabilities highly desirable in sensor networks [2]. Theoretically, a localization measurement device such as global positioning system (GPS) can be used for a sensor to locate itself. However, it is not practical to use GPS in every sensor node because a sensor network consists of thousands of nodes and GPS will be very costly. On the other hand, GPS does not work at all in indoor environments, so alternative solutions must be employed [3].

To solve the problem, many localization methods have been developed. Instead of requiring every node to have GPS installed, all localization methods assume only a few nodes be equipped with GPS hardware. These nodes are often called anchor nodes and they know their positions. Other normal sensors can communicate with a few nearby sensors and estimate distances between them using some localization algorithm [e.g. received signal strength (RSS), time of arrival (ToA)] and then derive their positions based on the distances [4].

WSN is treated as multi-model and multidimensional optimization problem and addressed through population based stochastic techniques. A few genetic algorithm (GA) based node localization algorithms are presented in [5, 6], that estimate optimal node locations of all one-hop neighbors. A two phase centralized localization scheme that uses simulated annealing (SA) Algorithm and GA is presented in [7]. Particle swarm optimization (PSO) based algorithm is proposed in [4, 8], to minimize the localization error. A two objective evolutionary algorithm which takes concurrently into account, during the evolutionary process, both the localization accuracy and certain topological constraints induced by connectivity considerations using meta heuristic approach, namely SA, is proposed in [9].

All these heuristic and meta-heuristic optimization algorithms are powerful methods for solving the node localization problem. The majority of these algorithms have been derived from behavior of biological systems and/or physical systems in nature. For example, PSO was developed based on the swarm behavior of birds and fish and while SA was based on annealing process of metals while GA was inspired by natural evolutions such as inheritance, mutation, selection and crossover. Each algorithm has its advantages and disadvantages.

A new meta-heuristic method named bat algorithm (BA) was proposed in [10] based on echolocation behavior of bats. BA has been developed to use the advantage of existing algorithms and other interesting features inspired by the fantastic behavior of echolocation of micro bats. BA is much superior to other existing algorithms in terms of accuracy and efficiency. The problem with the BA is that its success rate is very less because a bat is not able to explore all direction in the search space. Therefore to overcome this problem the existing BA is modified.

In modified bat algorithm (MBA), bat movement is modified with the chemotactic movement of bacterium, to find the optimal solution in that direction where bat movement can't. The proposed algorithm is better than the original bat algorithm in terms of computational speed and success rate of localized nodes because the MBA explores the search space more efficiently. This paper is organized as follows: Sect. 2 describes the brief overview of bat algorithm. Section 3 explains the modified bat algorithm. WSN

Localization is described in Sect. 4. Section 5 presents the simulation results and discussion while Sect. 6 gives the conclusion.

## 2 Bat Algorithm (BA)

Bat Algorithm, proposed by Yang [10], is a meta heuristic search algorithm inspired by fascinating abilities of bats such as finding their prey and discriminating different types of insects even at complete darkness. The advanced echolocation capability of bats makes them fascinating. Such abilities inspired to researchers on many fields. Bats use typical sonar called as echolocation to detect prey and to avoid obstacles. Bats, in particular micro-bats, are able to recognize positions of the objects by spreading high and short audio signals and by collision and reflection of these spread signals.

In BA, the echolocation characteristics are idealized within the framework of the following rules by benefitting such features of bats [10]:

- All bats use echolocation to sense distance, and they also 'know' the difference between food/prey and background barriers in some magical way;
- Bats fly randomly with velocity $v_i$ at position $x_i$ with a frequency $f_{min}$, varying wavelength and loudness $A_0$ to search for prey. They can automatically adjust the

Pseudo code for bat algorithm

1. Objective function $f(x), x = (x_1, \dots \dots \dots x_d)^T$
2. Initialize the bat population $x_i (i = 1,2,3 \dots \dots n) and\ v_i$
3. Define Pulse frequency $f_i\ at\ x_{i.}$
4. Initialize the rates $r_i$ and the loudness $A_i$
5. While ($t$< Max number of iterations)
6. Generate new solutions by adjusting frequency and updating velocities and locations/solutions according to equation (1), (2) and (3).
7. If $(rand > r_i)$
8. Select a solution among the best solutions
9. Generate a local solution around the selected best solution
10. End if
11. Generate a new solution by flying randomly
12. If $(rand < A_i) \& f(x_i < f(x^*))$
13. Accept the new solutions
14. Increase $r_i$ and reduce $A_i$
15. End if
16. Rank the bats and find the current best $x^*$
17. End while
18. Post process results and visualization

**Fig. 1** Pseudo code for Bat algorithm wavelength (or frequency) of their emitted pulses and adjust the rate of pulse emission $r_i$ [0,1], depending on the proximity of their target;

- Although the loudness can vary in many ways, it is assumed that the loudness varies from a large (positive) $A_0$ to a minimum constant value $A_{min}$.

Initially, bats with arbitrary positions and velocities are created in the search space. The new solutions $x_i^t$ and velocities $v_i^t$ at time step t are specified by Eqs. (1), (2) and (3).

$$f_i = f_{min} + (f_{max} - f_{min})\beta \tag{1}$$

$$v_i^t = v_i^{t-1} + \left(x_i^t - x^*\right)f_i \tag{2}$$

$$x_i^t = x_i^{t-1} + v_i^t \tag{3}$$

where $\beta \in [0,1]$ is a random vector drawn from a uniform distribution. Where $x^*$ is a existing global best location (solution) which is positioned after comparing all the solutions among all the n bats at each iteration. Primarily, each bat is randomly allocated a frequency

Pseudo code for Modified Bat Algorithm

1. Objective function $f(x), x = (x_1, \ldots\ldots\ldots x_d)^T$
2. Initialize the bat population $x_i (i = 1,2,3 \ldots\ldots n)$and $v_i$
3. Define Pulse frequency $f_i$ $at$ $x_{i.}$
4. Initialize pulse rates $r_i$ and the loudness $A_i$
5. While ($t$< Max number of iterations)
6. Generate new solutions by adjusting frequency and updating velocities and locations/solutions according to equation (1), (2) and (3).
7. Evaluate objective function. If solution is away from the optimal value of objective function then move to step 8 else jump to step 9.
8. Generate new solutions by following the chemotactic movement of bacterium (idea is taken from Bacterial Foraging Algorithm [11]) given in equation (4).
9. If $(rand > r_i)$
10. Select a solution among the best solutions
11. Generate a local solution around the selected best solution
12. End if
13. Generate a new solution by flying randomly
14. If $(rand < A_i \& f(x_i < f(x^*))$
15. Accept the new solutions
16. Increase $r_i$ and reduce $A_i$
17. End if
18. Rank the bats and find the current best $x^*$
19. End while
20. Post process results and visualization

**Fig. 2** Pseudo code for Modified Bat algorithm which is drawn uniformly from $[f_{min}, f_{max}]$. The pseudo code for bat algorithm is explained in Fig. 1.

BA can be considered as a balanced combination of the standard particle swarm optimization and the intensive local search controlled by the loudness and pulse rate.

## 3 Modified Bat Algorithm (MBA)

The original bat algorithm is modified using the bacterial foraging strategies. The new solutions are generated using the equations motivated by the concept of bacterial foraging algorithm (BFO). The movement of bacteria in the human intestine in search of nutrient-rich location away from noxious environment is accomplished with the help of the locomotory organelles known as flagella by chemotactic movement in either of the ways, that is, swimming (in the same direction as the previous step) or tumbling (in an absolutely different direction from the previous one) [11]. A detailed description of the complete bacterial foraging algorithm can be traced in [12, 13].

In the modified bat algorithm, the selection of bat movement is decided by the value of fitness function. If bat moves towards the optimum value of fitness function then type of bat movement is swimming. Otherwise bat follows the chemotactic movement of bacterium. The chemotactic movement of bacterium is represented by the following Eq. (4)

$$x_i^t = x_i^{t-1} + v_i^t \frac{\Delta_i}{\sqrt{\Delta_i^T \times \Delta_i}} \tag{4}$$

In the above equation, $v_i^t$ is the velocity at time step t calculated in Eq. (2) and $\Delta_i$ is the random number generated in the range $[-1, 1]$. Figure 2 shows the pseudo code for modified bat algorithm.

In the original bat algorithm, only swimming type movement is possible but in modified bat, swimming as well as tumbling is taken. Tumbling means bat moves in different direction (opposite direction) from the previous direction of bat. Chemotactic movement of bat is continued until a bat goes in the direction of its target (i.e. increasing/decreasing fitness). So, the basic idea behind the proposed scheme that in the absence of the tumbling movement, a bat is not able to explore all directions in the solution space may play a negative role.

## 4 WSN Localization Using BA and MBA

A single hop range based distributed techniques are used in WSN localization, to find the coordinate of maximum number of sensor nodes by using anchor nodes. To find the coordinates of *N* sensor nodes, the following procedure is followed.

Initially the *N* sensor nodes are randomly deployed in sensor field in C-shaped topology. The sensor nodes are composed of *M* anchors, which know their position as a priori, are also deployed in C-shape. $(N - M)$ are the unknown nodes, whose position is to be found. Each node has a communication range of R.

An unknown node can estimate its location if it has at least 3 non-coplanar anchor nodes in neighbor. That node is said to be localizable node. Each localizable node measures its distance from each of its neighboring anchors. The distance measurements are corrupted with Gaussian noise $n_i$, due to environment consideration.

$$\hat{d}_i = [d_i + n_i] \tag{5}$$

where $d_i$ is actual distance between the localizable node and anchor node which is given by

$$d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} \tag{6}$$

where as ($x$, $y$) is the location of the unknown node and ($x_i$, $y_i$) is the location of the ith anchor node in the neighborhood.

The position estimation of a given unknown node can be formulated as an optimization problem, involving the minimization of an objective function representing the localization precision. Therefore each unknown node which can be localized runs stochastic algorithms independently to localize itself by finding its coordinates ($x$, $y$). The objective function for localization problem is defined as:

$$f(x, y, z) = \frac{1}{M}\sum_{i=1}^{M}(d_i - \hat{d}_i) \tag{7}$$

where $M \geq 3$ (2D location of a node needs minimum 3 anchors) is the number of anchors with in transmission range, $R$, of the unknown node. The localization is an iterative procedure. The unknown nodes having at least 3 neighboring anchor nodes are localized first and the localized nodes are referred to anchors to assist the localization of the other unknown nodes. This process is repeated until there are no unknown nodes to be localized.

Each algorithm evolves the optimal location of unknown nodes, i.e. ($x$, $y$) by minimizing the error function. The localization error is defined as the distance between the real and estimated locations of an unknown node which is computed as the mean of square root of distance of computed node coordinates ($x_i$, $y_i$) and the actual node coordinates ($X_i$, $Y_i$) for $i = 1, 2, \ldots N_L$ ($N_L$ is the number of localized nodes) as shown below:

$$E = \frac{\sum_{i=M+1}^{N}\sqrt{(x_i - X_i)^2 + (y_i - Y_i)^2}}{(N_L)} \tag{8}$$

Localization error is normalized to units of node transmission range named mean localization error (MLE) to ensure application results. It is defined by the formula given in Eq. (9).

$$\text{Mean localization error (MLE)} = \frac{\sum_{i=M+1}^{N}\sqrt{(x_i - X_i)^2 + (y_i - Y_i)^2}}{(N_L)R} \tag{9}$$

**Table 1** Experimental set up values for WSN

| | |
|---|---|
| Random sensor nodes (n) | 200 |
| Anchor nodes (m) | 30 |
| Field area | $200 \times 200\ (\mathrm{m})^2$ |
| Ranging error | 5 % |
| Transmission range | 30 m |

## 5 Simulation Results and Discussion

To evaluate the performance of MBA, simulations are performed using MATLAB on a laptop of 16 GB memory and 3.5 GHz CPU to evaluate the performance of proposed algorithm. The unknown sensor nodes and anchor nodes are randomly deployed in C-shape over a square regular area. The transmission range of each sensor node is kept same. To find the effectiveness of modified bat algorithm, it is compared with the original bat algorithm. The experimental set up values for WSN scenario are shown in Table 1.

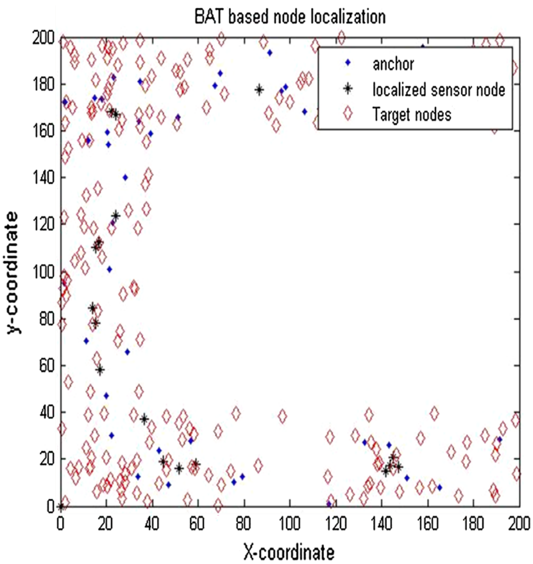



**Fig. 3** WSN Localization using Bat Algorithm

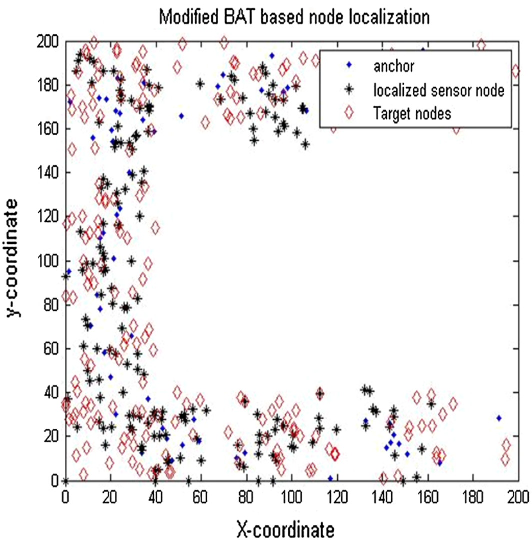



**Fig. 4** WSN Localization using Modified Bat Algorithm

**Table 2** Effect of anchor nodes

| Anchor | BA | | | Modified BA (MBA) | | |
|---|---|---|---|---|---|---|
| | MLE | Time (s) | NL | MLE | Time (s) | NL |
| 10 | 0.3314 | 10.14 | 6 | 0.5445 | 0.88 | 172 |
| 20 | 0.2427 | 10.92 | 7 | 0.5144 | 0.9 | 177 |
| 30 | 0.2809 | 11.98 | 7 | 0.5932 | 0.86 | 179 |
| 40 | 0.2561 | 13.5 | 8 | 0.5326 | 0.98 | 180 |
| 50 | 0.2888 | 13 | 9 | 0.5669 | 0.82 | 182 |
| 60 | 0.2658 | 12 | 10 | 0.5774 | 0.98 | 188 |
| 70 | 0.249 | 13.76 | 12 | 0.5264 | 0.79 | 188 |
| 80 | 0.2163 | 12.55 | 13 | 0.5084 | 0.87 | 193 |
| 90 | 0.2192 | 12.98 | 14 | 0.5374 | 0.86 | 194 |
| 100 | 0.2416 | 13.29 | 20 | 0.5101 | 0.96 | 195 |

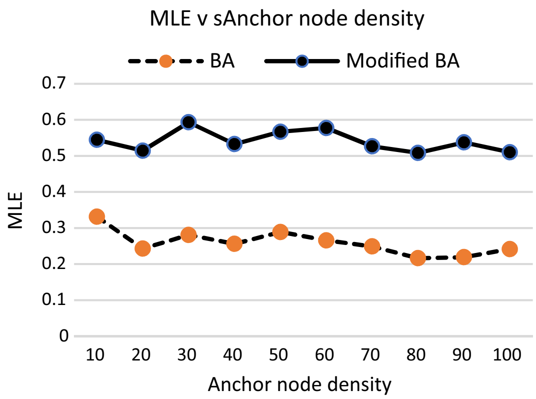



**Fig. 5** Effect of anchor node on MLE of BA and MBA

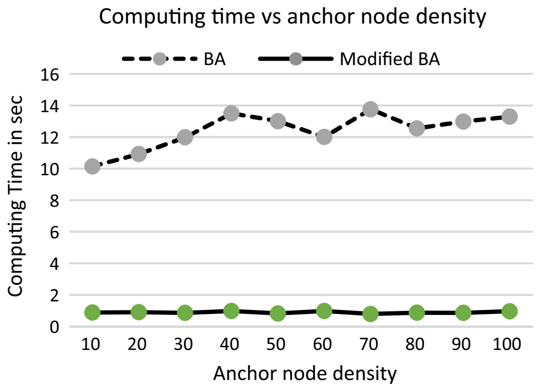



**Fig. 6** Effect of anchor node on Computing Time of BA and MBA

**Fig. 7** Effect of anchor node on localized node of BA and MBA

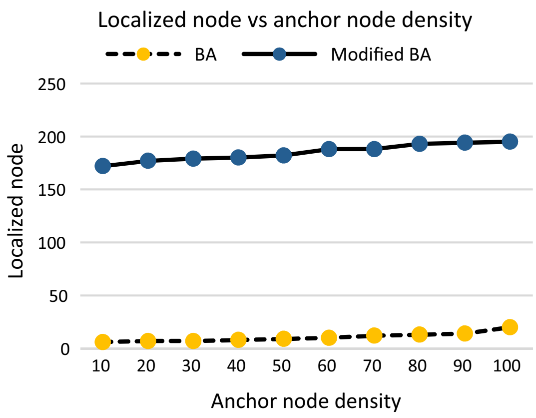
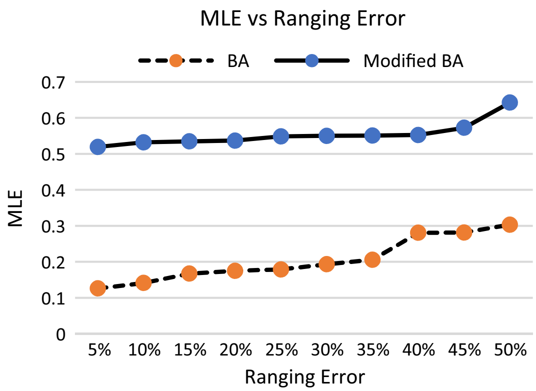



**Table 3** Effect of ranging error

| Ranging error (%) | BA | | | Modified BA | | |
|---|---|---|---|---|---|---|
| | MLE | Time (s) | NL | MLE | Time (s) | NL |
| 5 | 0.126 | 5.22 | 23 | 0.5191 | 0.89 | 197 |
| 10 | 0.1411 | 11.67 | 20 | 0.5319 | 0.85 | 190 |
| 15 | 0.1672 | 11.74 | 19 | 0.5346 | 0.98 | 190 |
| 20 | 0.175 | 11.75 | 18 | 0.5368 | 0.92 | 189 |
| 25 | 0.1788 | 11.76 | 15 | 0.5484 | 0.9 | 187 |
| 30 | 0.1932 | 12.68 | 14 | 0.5499 | 0.87 | 187 |
| 35 | 0.2056 | 12.88 | 13 | 0.5506 | 0.93 | 186 |
| 40 | 0.2806 | 12.88 | 13 | 0.5522 | 0.88 | 183 |
| 45 | 0.2813 | 12.93 | 12 | 0.5723 | 0.98 | 180 |
| 50 | 0.303 | 14.25 | 11 | 0.6424 | 0.81 | 171 |

**Fig. 8** Effect of ranging error on MLE of BA and MBA



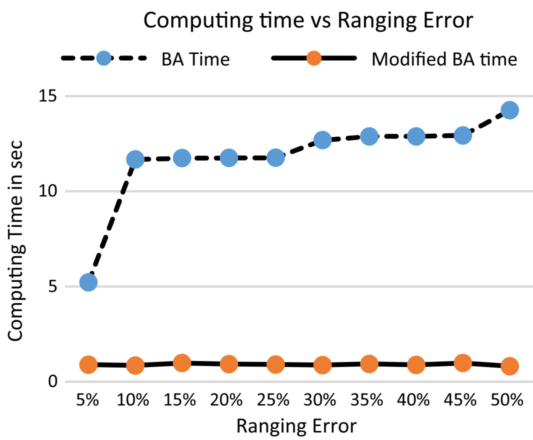



**Fig. 9** Effect of ranging error on Computing Time of BA and MBA

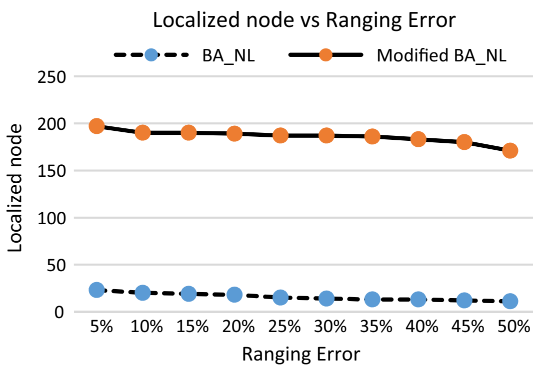



**Fig. 10** Effect of ranging error on localized node of BA and MBA

### 5.1 Parameters Setup

To compare the proposed algorithm with the existing bat algorithm, the objective function evaluation is computed P × I times, where P is the population size and I is the maximum number of iterations (unless optimum was reached earlier). The population size is set to 20 and the number of iterations is set to 100 for both algorithms. Besides these common control parameters, each of mentioned algorithms has additional control parameters that directly improve their performance. For both the proposed modified bat algorithm and existing BA, the additional control parameters $f_{min}$ and $f_{max}$ are set to 0.01 kHz and 0.05 kHz respectively. The initial values for parameters pulse rate (r) and loudness (A) are taken 0.5 and 0.2  ms, respectively.

### 5.2 Quality and Computational Analysis of Results

Wireless sensor network localization using existing bat and modified bat algorithms are shown in Figs. 3 and 4. The first conclusion that can be drawn from the Figs. 3 and 4 is that the proposed algorithm has higher success rate because it localizes more number of target nodes as compared to the existing bat algorithm.

**Table 4** Mean localization error values for both algorithms for 30 trials

| Trials | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| BA | 0.2397 | 0.2922 | 0.1948 | 0.167 | 0.2447 | 0.1935 | 0.1964 | 0.2414 | 0.1632 | 0.4429 |
| MBA | 0.5364 | 0.548 | 0.5385 | 0.5373 | 0.4753 | 0.6188 | 0.5515 | 0.5766 | 0.5391 | 0.5297 |
| Trials | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
| BA | 0.1455 | 0.2282 | 0.2315 | 0.1845 | 0.2244 | 0.1736 | 0.2844 | 0.2246 | 0.1611 | 0.1215 |
| MBA | 0.5476 | 0.575 | 0.5529 | 0.5727 | 0.537 | 0.527 | 0.5753 | 0.591 | 0.561 | 0.499 |
| Trials | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 |
| BA | 0.1649 | 0.3415 | 0.2516 | 0.1845 | 0.2244 | 0.1736 | 0.2844 | 0.2282 | 0.1935 | 0.2315 |
| MBA | 0.5085 | 0.526 | 0.5126 | 0.5503 | 0.5476 | 0.575 | 0.5529 | 0.5297 | 0.54753 | 0.5753 |

**Table 5** Minimum, maximum, average and SD for BA and MBA

| | Min | Max | Avg. | SD |
|---|---|---|---|---|
| BA | 0.1215 | 0.4429 | 0.226279 | 0.074037 |
| MBA | 0.4753 | 0.6188 | 0.546297 | 0.030997 |

Output parameters of WSN Localization are computed for different number of anchor nodes. Distribute 200 target nodes in the simulation area and the anchor nodes are varying from 10 to 100. Having more number of anchors is advantageous because it gives more number of references for unknown nodes. The number of nodes that get localized depends on the number of anchors.

Table 2 reports the mean localization error (MLE), average CPU time taken by both algorithms and number of target nodes localized by modified BA and existing BA algorithms. From Table 2, we can see that as the number of anchor nodes are increasing, the number of localized nodes and computing time is increasing but MLE is decreasing for both algorithms.

The results of Table 2 are represented by the following figures individually. In comparison to each other, for the same number of anchor nodes and same WSN configuration, MBA is inferior to BA in terms of MLE shown in Fig. 5. But on the other hand MBA has better results like computing time and success rate to localize more number of target nodes than the BA algorithm, is represented in Figs. 6 and 7.

Ranging error, the maximum amount of Gaussian additive noise associated with distance measurements, is an important parameter that influences the accuracy of localization. It is expected that the mean localization error increases as ranging error increases, thus leading to decrease in accuracy. The dependence of MLE on ranging error is studied over 30 trial runs for each value of error from 5 to 50 %. Convergence speed and number of localized nodes (NL) are also varied with respect to ranging error. In Table 3, the effect of ranging error on MLE, Computing time, number of localized nodes (NL) is presented for proposed bat algorithm and existing BA algorithm.

It is concluded from Fig. 8 that for the same value of ranging error, the proposed algorithm has higher value of MLE than the existing BA algorithm. But the proposed algorithm is better than the existing one in terms of convergence speed and success rate. Because MBA has less computing time and has capability to localize more number of localized nodes than existing BA algorithm, shown in Figs. 9 and 10, respectively.

Both the algorithms are stochastic; so, one can't expect the same solution in all trials even with identical deployment. This is the reason, why the results of 30 trial runs are taken. The mean localization errors are calculated for both the algorithms for 30 trials shown in Table 4. The standard deviation is calculated for these values given in Table 5. From the results it is concluded that the modified bat algorithm is more robust than bat algorithm.

## 6 Conclusion

The original bat algorithm has good accuracy because it has less mean localization error than the proposed algorithm. But the convergence rate (computing time) and success rate (number of localized nodes) of this algorithm is not so good. To improve these two parameters, bat algorithm is modified by taking the idea from chemotactic movement of bacterium of bacterial foraging algorithm. The proposed algorithm is applied on WSN Localization problem. From the results, it can be concluded that the modified bat algorithm has better convergence rate (less computing time) and high success rate (more number of localized nodes) as compared to original bat algorithm. In addition to this, Consistency is also very important parameter for practical application. The simulation results show that modified bat algorithm is more consistent (robust) than the original bat algorithm.

In the future work further research emphasizes the performance comparison of the proposed algorithm with other popular methods for WSN localization problem. In addition, hybridization with other algorithms may also prove to be fruitful.

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