Multistage Localization in Wireless Sensor Networks using Artificial Bee Colony Algorithm

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***Abstract*—Accurate localization of randomly deployed sensor nodes is critically important in wireless sensor networks (WSNs) deployed for monitoring and tracking applications. The localization challenge has been posed as a multidimensional global optimization problem in earlier literature. Many swarm intelligence algorithms have been proposed for accurate localization. The untapped vast potential of the artificial bee colony (ABC) algorithm has inspired the research presented in this paper. The ABC algorithm has been investigated as a tool for anchor-assisted sensor localization in WSNs. Results of Matlab simulation of ABC-based multistage localization have been presented. Further, the results are compared with those of the localization method based on the particle swarm optimization (PSO) algorithm. A comparison of the performances of ABC and PSO algorithms has been presented in terms of the number of nodes localized, localization accuracy and the computation time. The results show that the ABC algorithm delivers higher accuracy of localization than the PSO algorithm does; but, it takes longer to converge. This results in a trade off between speed and accuracy of localization in WSNs.**

I. Introduction

Wireless sensor networks (WSNs) are networks of distributed autonomous devices that are deployed in large numbers to monitor physical or environmental conditions. A WSN consists of a collection of smart motes that can sense, compute, and communicate over wireless medium. Motes are small, inexpensive and they have limited memory and computing resources [1]. WSNs are deployed to monitor outdoor phenomena, such as vehicular traffic, wildlife migration, seismic seizures, landslides, avalanches and volcanic eruptions. They are also used to monitor indoor phenomena, such as structural health, temperature profile, intensity of radioactivity and noise levels. In many applications, sensor motes are deployed randomly at locations that are not pre-determined. They may be deployed in inaccessible or harsh mission fields for applications, such as disaster-relief [2]. In these applications, sensor location information is critical for the mission's objectives and for the efficient operation of WSNs [3]. Creating location awareness in each deployed sensor node is referred to as localization. Sensor locations play an important role in assessing coverage and connectivity and in location-based WSN routing protocols [4].

Accurate localization of sensor nodes has a strong influence on the performance of WSNs. The simplest way to obtain location information is to equip each node with a global positioning system (GPS) receiver. However, this method is neither practical in indoor applications, nor feasible because of size, cost and power constraints on motes. GPS-less localization is a popular research topic for over a decade. Many localization algorithms estimate the location of unknown nodes using special nodes called anchors or beacons which have *a priori* knowledge of their locations [3], [5]. Most measurement techniques used for localization involve the following steps [6]:

1) Distance or angle estimation: Distances and/or angles between two nodes are estimated through received signal strength indication (RSSI), time of arrival (ToA), time difference of arrival (TDoA), angle of arrival (AoA), and communication range.
2) Location estimation: This involves computing a node's position based on available information concerning distances/angles and positions of anchor nodes using methods such as trilateration, triangulation and multilateration.
3) Localization: In this step, the available information is manipulated in order to allow most or all nodes to estimate their locations. In multistage localization algorithms, the nodes that estimate their locations in a stage are used as anchors to help their neighbor nodes to localize in the next stage.

Apart from measurement-based localization methods, there are many conventional approaches as range-free anchor-based centroid methods that use distance vector algorithms to propagate the location information among unknown nodes. Measurement of parameters in these methods may not be exact due to noise and estimation errors. Therefore, results of such localization algorithms are likely to be inaccurate [7].

The localization problem has been formulated as a global optimization problem in [7]. Several deterministic and heuristic solutions have been proposed. Biologically-inspired heuristic algorithms have been used because of their simplicity, resource-efficiency and speed [8]. Swarm intelligence (SI) techniques, such as particle swarm optimization (PSO) and bacterial foraging algorithm have been used successfully in sensor node localization [5], [7]. SI techniques are based on the behavior of a biological social system, such as a flock of birds, a school of fish, or colonies of bees or ants. The artificial bee colony (ABC) algorithm is a relatively newer member of the SI family of algorithms.

The ABC algorithm has been proposed for multistage node localization in this paper. ABC is a metaheuristic search algorithm inspired by intelligent foraging behavior of honey bees in nature [9]. In this algorithm, a swarm of artificial bees move randomly in an n-dimensional search space and interact with each other to search for an optimal solution. In this research, the ABC algorithm has been used to determine the locations of sensor nodes using *a priori* knowledge of anchor nodes and estimated distances between the former and the latter. Multiple trials of ABC-based multistage localization have been simulated and the results have been presented. The results have been compared with those of the PSO-based iterative localization presented in [7]. Since PSO algorithm and its applications have been very well discussed in literature, it has not been detailed in this paper.

The following are the primary contributions of this paper :

1) The formulation of sensor localization as an optimization problem has been recaptured.
2) The ABC algorithm has been investigated as a tool that minimizes the errors in estimating sensors' locations.
3) Details of numerical simulation have been presented.
4) Results of the ABC algorithm have been presented with accuracy and speed of localization as major figures of merit.
5) A comparative analysis of ABC- and PSO-based localization has been performed.

The remainder of this paper has been organized as follows: Previous research in sensor localization and the ABC algorithm has been surveyed in Section II. An overview of the multistage localization process has been presented in Section III. The ABC algorithm has been outlined in Section IV. Details of numerical simulation and the results obtained have been presented in Section V. In addition, a comparison of ABC- and PSO-based localization has been presented in Section V. Finally, concluding remarks and suggestions for future research have been given in Section VI.

II. Related Work

Anchor-assisted sensor localization has evoked significant research interest in the recent past. Several methods and algorithms have been proposed and compared on the basis of localization error, necessary numbers of anchors, numbers of localized nodes, etc. Typical localization algorithms require the measurement of distances between anchors and sensors. Various methods have been proposed to measure these parameters. An overview of measurement-based techniques in sensor node localization has been presented in [10]. Most measurement-based approaches rely on some form of communication between anchors and unknown nodes. In the approach proposed in [11], RSSI is used to estimate the distances between immediate neighbors of anchors. Unknown nodes use propagation methods like distance vector (DV-hop, DV-distance or Euclidian distance) to share the location information with their one-hop neighbors. The second-hop neighbors approximate their distances to anchors. The exchange of the information among immediate neighbors is continued until the entire network is localized.

The measurement schemes are prone to noise; and thus, they result in localization errors. An alternative approach to the location estimation is to model errors as random variables as proposed in [12]. When a node receives the location of an anchor, it is not treated as the exact location. An unknown node receives the position information from multiple anchors and then estimates its location. This approach suffers from high computational cost. In addition, it is not viable to equip all the unknown nodes with ranging capability when WSNs are largely populated [13]. A GPS-less localization in unconstrained outdoor environments is presented in [14]. In this approach, the localization is based on radio model in which each node connects itself to the centroid of a set of approximate reference points using a connectivity metric. This method does not require coordination among anchors and unknown nodes. Another approach to reduce cost and power burdens of GPS is to install it on a mobile anchor which broadcasts its coordinates. This approach helps to localize the unknown nodes near mobile anchors. A survey on mobile anchor-based localization has been presented in [15]. Localization is an unconstrained optimization problem; therefore, many computationally intelligent localization algorithms have been proposed [8]. These algorithms have been compared with respect to localization accuracy, computational efforts, communication overheads and the required anchor density metrics.

Localization techniques, Gauss-Newton algorithm (GNA) and PSO have been proposed in [16]. In these techniques, a person deploys sensor nodes with the help of a pedometer and an electronic compass. Sensor nodes exchange anchor information using RSSI and use GNA and PSO algorithms for localization. Both GNA and PSO search the same optimum location with the same set of measurements. But GNA, being a local optimization method, shows poorer result when the stopping criteria are met or when the pedometer error is higher. In localization process, PSO shows more accurate position estimation than GNA and it is more robust. GNA is occasionally unstable during iterations due to matrix inversion computation and is only feasible with a pedometer having good accuracy. Localization algorithms that use genetic algorithm (GA), fuzzy logic system (FLS) and neural network (NN) have been developed for indoor and outdoor WSNs applications in [17]. GA is a numerical optimization algorithm inspired from genetics that comprises of selection, crossover, and mutation. GA is simple, yet it provides an adaptive and robust optimization. FLS produces acceptable but definite output in response to inaccurate input and NN is used for mapping all the sensors nodes from anchors.

ABC is a recent multidimensional optimization algorithm. Its advantages include the ease of implementation and high quality solutions. The study presented in [9] focuses on the comparison of ABC, PSO, GA and the differential evolution algorithm. These algorithms are tested on a large set of numerical benchmark functions and results show that the performance of the ABC is better than or similar to those of other population-based algorithms. The ABC algorithm has been successfully used for the dynamic deployment of sensor nodes for optimal coverage in [18].

A hybrid algorithm of ABC and GA has been proposed to determine the shortest path of mobile anchor to localize all sensors has been presented in [19]. The hybrid algorithm has advantages of strong global search capability, satisfactory accuracy and quick convergence to optimal location. ABC has been also applied in clustering in routing protocols in WSNs. ABC can achieve optimum data grouping process and shows similar results with PSO-based protocols and routing protocols as low-energy adaptive clustering hierarchy in WSN [20]. A combination of ABC with DV routing algorithm (ABCDV) has been proposed in [21]. ABCDV reduces position error without increasing the hardware overhead at each node. ABCDV-hop routing can improve the calculation method of average distance per hop of anchor nodes and give better results than traditional DV routing. The sensor deployment problem is modeled as a data clustering problem and ABC is applied to get a optimal solution to the deployment in [22].

The ABC has also been used to train radial basis neural networks for precise traffic flow prediction [23], to provide an effective local search technique in quality-of-service selection [24], to find spatial transformation using similarity metrics in image registration [25] and to optimize power in data centers in cloud computing [26]. The unexploited abundant application potential of ABC has inspired the research reported in this paper. The ABC algorithm has been proposed for multistage node localization in WSNs.

III. Multistage Localization Algorithm

The deployment scenario considered in this study is as follows: A total of N nodes are deployed in a plane square mission field. Each node has a communication range of r units. A small percentage of the nodes are special nodes called anchors or beacons. Anchors know their locations because either they have GPS hardware or they are deployed at known locations. The rest of the nodes are deployed at random locations; therefore, they do not have location awareness. They are called dumb, unsettled or unknown nodes. The numbers of anchors and unknown nodes are A and U, respectively, so that $N = A + U$. The anchors are named as $a_1, a_2, a_3, \ldots, a_A$. Their locations are $(a_{1x}, a_{1y}), (a_{2x}, a_{2y}), \ldots, (a_{Ax}, a_{Ay})$, respectively, where x and y are the natural coordinates of the mission field. The anchor a_i broadcasts its coordinates (a_{ix}, a_{iy}) periodically. The dumb nodes are named as $u_1, u_2, u_3, \ldots, u_U$. Their locations are $(u_{1x}, u_{1y}), (u_{2x}, u_{2y}), \ldots, (u_{Ux}, u_{Uy})$, respectively. Each dumb node u_i aims to estimate its location (u_{ix}, u_{iy}) as accurately as possible. This is the crux of the localization problem [7].

A dumb node that has at least three non-collinear anchors in its communication range estimates its distances from them by measuring parameters, such as RSSI, ToA and TDoA. If the node does not have three non-collinear anchors in its range, it cannot be localized. Each localizable node executes the ABC algorithm to estimate the coordinates of its location. Estimates of distances from anchors and locations of the anchors are the input arguments to the ABC algorithm. The goal of the localization algorithm is to determine the locations of all or as many dumb nodes as possible. Each node u_i estimates its location (u_{ix}, u_{iy}) independently without any help from a central node. Therefore, the distributed localization problem translates into a two-dimensional optimization problem.

The number of localized and unlocalized nodes are denoted by L, and N_L, respectively ($\therefore L + N_L = U$). The multistage localization algorithm presented here progresses in stages $s_1, s_2, \ldots, s_T$. Initially in stage s_1, L_1 nodes estimate their locations. These nodes act as anchors in the second stage s_2. Therefore, the number of anchors in s_2 is $s_2 = A + L_1$. Due to the increased number of anchors, more dumb nodes may get localized in s_2. Thus, the number of anchors in stage s_3 increases to $A + L_1 + L_2$. This stage-by-stage localization terminates in stage s_T when the number of unlocalized nodes equals zero or equals the number of unlocalized nodes in the previous stage $s_{(T-1)}$. The proposed method can be divided into two phases.

A. Distance Estimation

In this phase, each unknown node u_j, $j = 1, 2, \ldots, U$, estimates its distances $\hat{d}_i$ from anchors a_i, $i = 1, 2, 3$, in its communication range. Estimation of distances involves the measurement of the aforementioned parameters. This method of distance estimation is prone to errors. Therefore, the distances are estimated as $\hat{d}_i = d_i + g$, where d_i is obtained as in (1) and g is the additive noise.

$$d_i = \sqrt{(a_{ix} - u_{jx}) + (a_{iy} - u_{jy})} \tag{1}$$

The additive noise represents environmental uncertainties associated with erroneous estimation. The additive noise g is generated using (2).

$$g = p\left(\frac{e}{100}\right)(-1)^q \tag{2}$$

Here, e is the noise percentage (higher e represent more severe environmental uncertainties). The parameter p is a random number distributed uniformly between 0 and 1, and q is 0 or 1, chosen randomly.

B. ABC Optimization

In this phase, each unknown node u_j that has three non-collinear anchors in its range obtains $(\hat{u}_{jx}, \hat{u}_{jy})$, the estimates of the coordinates of its location, using the ABC optimization algorithm. A node that has more than three anchors in its range chooses the nearest three anchors. The ABC algorithm computes the estimated location $(\hat{u}_{jx}, \hat{u}_{jy})$ in such a way that the mean localization error E_{jl} expressed in (3) is minimum.

$$E_{jl} = \frac{1}{3}\sum_{i=1}^{3}\left(\sqrt{(\hat{u}_{jx} - a_{ix})^2 + (\hat{u}_{jy} - a_{iy})^2} - \hat{d}_i^{\,2}\right) \tag{3}$$

The localization error E is used as the measure of the effectiveness of the algorithm. E is determined when the multistage localization terminates. It represents the mean of the distances between actual node locations (u_{jx}, u_{jy}) and the estimated node locations $(\hat{u}_{jx}, \hat{u}_{jy})$, as expressed in (4).

$$E = \frac{1}{L}\sum_{j=1}^{L}\left(\sqrt{(u_{jx}-\hat{u}_{jx})^2+(u_{jy}-\hat{u}_{jy})^2}\right) \tag{4}$$

Here, L represents the number of localized nodes. The remaining $U-L$ nodes are not localized because they do not have three non-collinear anchors nodes in their communication range.

IV. The ABC Algorithm

The ABC algorithm is based on natural colonies of honey bees that have self-organization and co-ordination skills in their foraging behavior. Honey bees in nature use a mechanism of waggle dance to optimally locate food sources and search for new ones. This natural behavior inspired the development of the intelligent search algorithm ABC [9]. The ABC algorithm aims at finding the optimal solution to a continuous optimization problem in an iterative manner. The objective of an optimization algorithm is to minimize or maximize a real-valued fitness function $f(x)$ by systematically choosing the values of variables from an allowed D-dimensional set A. Given $f(x): A \subseteq \mathbb{R}^D \rightarrow \mathbb{R}$, an optimization algorithm seeks to determine an element x^* in A such that $f(x^*) \geq f(x)\ \forall\, x \in A$ and $f(x^*) \neq \infty$. In the localization problem, each sensor node estimates two coordinates of its location in the plane of deployment such that the localization error defined in (3) is minimum. Therefore, $D = 2$, and the objective function is $f(x) = E_{jl}$ as expressed in (3).

The ABC algorithm consists of a swarm of S bees created in the D- dimensional space. Bees are assigned to food sources which represent the possible solutions. The amount of the nectar at a food source represents the fitness or quality of the solution. The colony of artificial bees consists of the three groups of bees: Employed bees, Onlooker bees and Scout bees. The ABC algorithm uses following steps for all the three categories of bees in one cycle. Details of these steps are given below: [27]

A. Initialization Step

In this step, values as maximum population S, dimension D, maximum cycles $k_{\max}$, and lower limit and upper limit $x_{\min}$, $x_{\max}$ are initialized. Food source is a D dimensional vector represented as $x_{1D}, x_{2D} \ldots x_{SD}$. B is a constant value representing a maximum limit to search for food positions. T is initialized to 0 for keeping count of number of trials a bee searches for x_i in a given $k_{\max}$. Bees evaluate the given objective function with initial random food positions to determine the fitness f_x of each x_{iD} where $i = 1, 2, 3 \ldots, S$. Each employed bee explores its neighboring food sources and apply a greedy selection strategy between its food source and food sources of its neighbors. If the fitness of the new position is higher, then the employed bee updates its x_{iD}. Otherwise, it remains unchanged.

B. Onlooker Step

A probability value is p_i is associated with each onlooker bee. Onlooker bee chooses a food source with the probability which is proportional to its quality. Different schemes can be used to calculate probability values as roulette wheel selection method or the expression given in (5).

$$p_i = \frac{f_i}{\sum_{i=1}^{N} f_i} \tag{5}$$

New candidate positions from the existing memory are generated using (6).

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{oj}) \tag{6}$$

Here $i, o \in 1, 2, 3, \ldots, N$ and $j = 1, 2, \ldots, D$. Index o is randomly chosen such that $o \neq i$ and $-1 \leq \phi_i \leq 1$. If the new solution is outside the boundary of the search space, then it is set to the boundary, $x_{\min}$ or $x_{\max}$.

C. Scout Step

A control parameter B is used to abandon the food source. The position of food sources cannot be improved when a count of predetermined trials (T) exceeds B. This is where scout bees are generated. Scout bees discover new food position and randomly replace existing food position as given in equation (7), where q is a random number, in the range $[0, 1]$.

$$x_{ij} = x^j_{\min} + q(x^j_{\max} - x^j_{\min}) \tag{7}$$

These steps are repeated until the desired solution is found or a predefined maximum number of cycles is reached. Each employed bee is associated with only one food source. Thus the number of employed bees is equal to the number of food sources which correspond to solutions of a given problem. Pseudocode for the ABC algorithm has been presented in Algorithm 1.

Division of labor is an important feature of ABC that serves as a basis to allocate tasks in any artificial system [28]. The ABC algorithm is adaptable, stable and does not commit its activities along excessively narrow channels [29].

V. Numerical Simulations and Results

ABC-based multistage localization proposed here has been validated through MATLAB simulations on a Windows–7 computer having Intel® Core™ i5 processor @ 3.20 GHz and 8 gigabytes of RAM. The sensor field parameters used in the ABC-based multistage localization are as below:

1) Communication radius $r = 30$ units;
2) Area of the deployment field is 100×100 square units;
3) Number of Anchors $A = 10$;
4) Number of unknown nodes $U = 50$;
5) Percentage of error $e = 2$;
6) It is ensured that no three anchors are collinear.

Algorithm 1 The pseudocode of the ABC algorithm

1: Initialize x_{ij} randomly such that $x_{\min} \leq x_{ij} \leq x_{\max}$ and $i : 1, 2, 3, \ldots, S$ and $j : 1, 2, 3, \ldots, D$;
2: Evaluate cost of the objective function H_x and calculate fitness f_x;
3: $f_x = \frac{1}{(1+f_x)}$ if $H_x \geq 0$
4: $f_x = 1 + |(f_x|$ if $H_x < 0$
5: Iteration $k = 1, T = 0, B = 100$;
6: **while** ($k \leq k_{\max}$) **do**
7:     Select o;
8:     Select random food source x_{ij} and generate a new food v_{ij} using (6);
9:     Calculate fitness f_v;
10:     **if** $f_v > f_x$ **then**
11:         $v_{ij} = x_{ij}$;
12:         $f_x = f_v$;
13:         $H_x = H_v$;
14:         $T = 0$;
15:     **end if**
16:     **if** $f_v < f_x$ **then**
17:         $T = T + 1$;
18:     **end if**
19:     Calculate probabilities p_i for a new solution using (5) or roulette wheel selection strategy;
20:     Produce new solutions v_{ij} for onlookers using the value of p_i and the existing solutions x_{ij};
21:     Store global optimal solution (g) and its position (x_{ij});
22:     Repeat steps 9 through 18 for onlookers v_{ij};
23:     **if** $T \geq B$ **then**
24:         Determine the scout bees' position using (7);
25:     **end if**
26:     $k = k + 1$;
27: **end while**
28: Global optimum = g

Each target node runs the ABC algorithm to localize itself. The parameter used in ABC are:

1) Population of bees $S = 30$;
2) Dimensionality $D = 2$;
3) Limit for elimination of bees $B = S \times D$;
4) Maximum iterations $(k_{\max}) = 100$;

These parameters are finalized through several trials. The results of 6 trial runs conducted have been presented in Table I. Here, L_{si} refers to the number of localized nodes in stages $i = 1, 2, 3, 4$. Similarly, E_{si} and T_{si} refer to the average error and localization time in stage s_i, respectively. The number of localized nodes L_{si} increase with every stage, as the localized nodes act as anchor nodes for the next stage. However, the process of localization can terminate prematurely when certain nodes do not get three anchor in their communication radius. This scenario is shown in the sixth trial run in Table I. The table shows that ABC produces acceptably good localization. The initial deployment of sensor nodes and anchors in a trial has been depicted in Figure 1(a). An intermediate stage of localization, where some of the nodes are localized has been illustrated in Figure 1(b). The final stage of the localization has been presented in Figure 1(c).

TABLE I
RESULTS OF SIX TRIAL RUNS OF ABC-BASED MULTISTAGE LOCALIZATION

Trial	Parameters	Stage 1	Stage 2	Stage 3	Stage 4
1	L_{si}	18	41	49	50
	E_{si}	0.1601	0.0908	0.0599	0.0569
	T_{si}	1.6147	4.9511	8.4829	10.8954
2	L_{si}	18	41	48	50
	E_{si}	0.1351	0.101	0.0478	0.0505
	T_{si}	1.567	5.3218	9.404	12.7638
3	L_{si}	26	48	50	
	E_{si}	0.2344	0.0957	0.0633	
	T_{si}	2.0999	6.0415	9.5343	
4	L_{si}	20	50		
	E_{si}	0.3648	0.1936		
	T_{si}	1.7372	5.5655		
5	L_{si}	23	48	50	
	E_{si}	0.5063	0.1114	0.0542	
	T_{si}	1.8653	5.9459	9.3619	
6	L_{si}	25	46	† 46	
	E_{si}	0.1982	0.0623	0.0620	
	T_{si}	8.8919	15.7753	26.2821	

† Four nodes remained unlocalized.

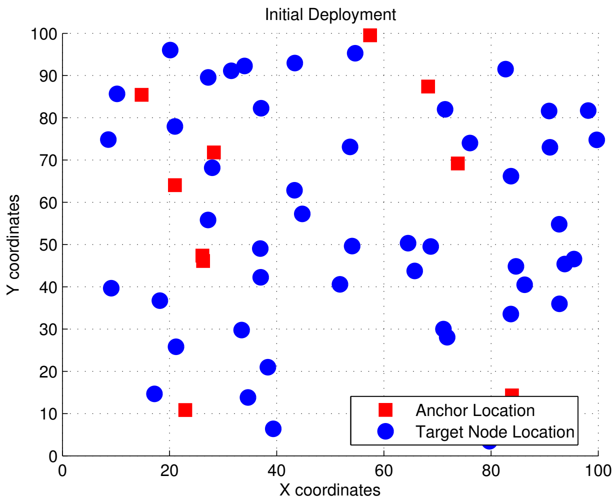
The results of ABC-based multistage localization have been compared with PSO-based localization algorithm presented in [7]. The PSO-based iterative localization algorithm has been implemented on the same computer mentioned above. The sensor-field parameters are identical. The parameters used in PSO are:

1) Population of particles = 30;
2) Maximum number of iterations = 100;
3) Limits of search space, $x_{\min} = 0$ and $x_{\max} = 100$;
4) Acceleration constants $C_1 = C_2 = 2$;
5) Inertia weight ω is decreased linearly from 0.9 in the first iteration to 0.4 in the 100^{th} iteration.

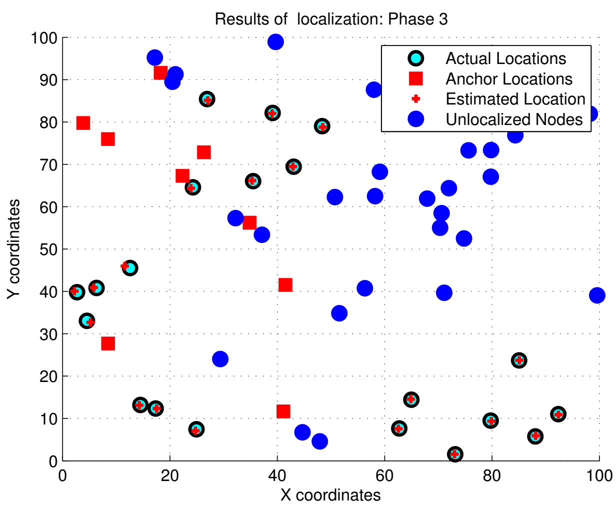
These parameter are chosen as per the recommendation in [7]. A comparison of the results of ABC- and PSO-based localization are presented in Table II. Results show that the ABC algorithm achieves higher quality of localization. However PSO takes less computation time.

Localization error in each stage is related to the noise associated with distance measurement. The dependence of localization error on the percentage noise has been depicted in Figure 2. Percentage of noise depends upon the environmental uncertainties, such as electrical interferences, number of obstacles and varying channel characteristics. It is difficult to predict the noise in the receiver's hardware by a mathematical method. The plot presented in Figure 2 shows that the localization error increases with the noise.

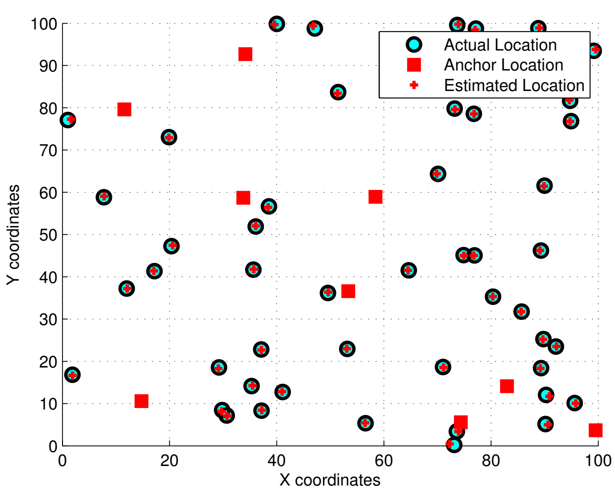
ABC and PSO are the heuristic optimization algorithms. It would be interesting to compare their performances using statistical analysis of their results in several trial runs. In another case study, ABC and PSO algorithms are experimented



(a) Initial Deployment



(b) Intermediate Stage of Localization



(c) Final Stage of Localization (Fully Localized WSN)

Fig. 1. Stages of ABC-based multistage localization in a trial run

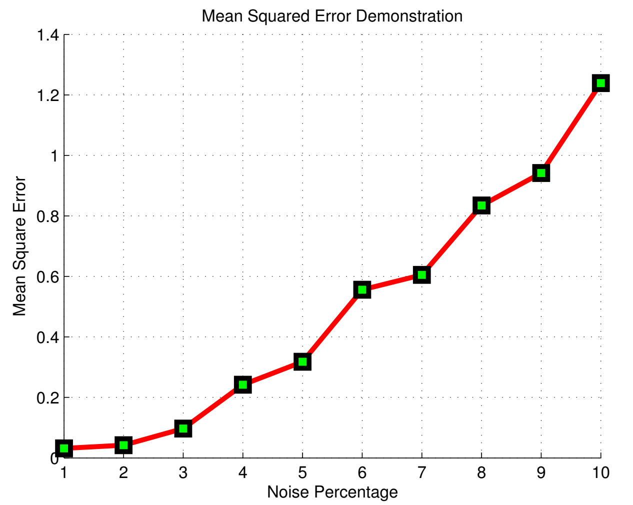


Fig. 2. Dependance of the localization error on the severity of environmental noise

TABLE II
COMPARISON OF RESULTS OF ABC- AND PSO-BASED LOCALIZATION IN SIX TRIAL RUNS EACH

Trial	# s_i	Ls_i		Esi		Tsi	
		ABC	PSO	ABC	PSO	ABC	PSO
1	1	12	12	**5.326**	62.9468	0.9131	**0.4641**
	2	29	29	**0.1603**	0.1788	3.0549	**1.5938**
	3	45	45	**0.1096**	0.1112	6.5221	**3.3756**
	4	50	50	**0.0671**	0.1067	9.7095	**5.0519**
2	1	10	10	**0.2557**	1.5730	0.7638	**0.3779**
	2	37	36	**0.1674**	0.2576	3.3657	**1.675**
	3	46	49	**0.0707**	0.0797	7.4869	**3.9655**
	4	50	† 49	**0.0514**	0.0764	10.2082	**5.6251**
3	1	14	14	**0.1593**	0.1637	1.0555	**0.5196**
	2	48	48	**0.1701**	0.1756	4.7589	**2.4302**
	3	50	50	**0.0442**	0.0578	8.566	**4.4870**
4	1	13	13	**0.1281**	0.2320	1.082	**0.5299**
	2	37	37	**0.0896**	0.1065	3.9348	**1.9922**
	3	50	50	**0.0427**	0.0526	8.2801	**4.3295**
5	1	19	19	**4.9617**	83.4785	1.3716	**0.6882**
	2	49	48	**0.0844**	0.0946	4.9280	**2.4739**
	3	50	50	**0.0641**	0.0690	8.3987	**4.2766**
6	1	10	10	**0.3136**	0.3602	0.7427	**0.3751**
	2	33	33	**0.1096**	0.1309	3.2258	**1.6279**
	3	48	48	**0.0607**	0.0699	6.8351	**3.5330**
	4	50	50	**0.0363**	0.0864	10.4016	**5.3985**

† One node remained unlocalized in PSO-based localization.

on with the same number of unknown nodes and anchors. To determine average and standard deviation in localization error and computing time of ABC and PSO-based localization, it is necessary that all the nodes are localized in a single stage. In order to ensure this, the communication radius r is set to a large value, 300 units. The summary of the results of 30 trials is given in Table III.

It can be observed that the ABC algorithm estimates sensor locations more accurately than PSO. But, its computing time is significantly more than PSO's. There is a trade off between

TABLE III
STATISTICAL SUMMARY OF 30 TRIAL RUNS OF ABC- AND PSO-BASED WSN NODE LOCALIZATION.

	Localization Error		Computing Time	
	Mean	Standard Deviation	Mean	Standard Deviation
ABC	**0.0112**	**0.1635**	15.8392	0.2764
PSO	0.0222	0.1865	**6.8494**	**0.0409**

For all trials, $e = 2$, $A = 10$ and $U = 50$.

the accuracy and the speed of localization. The choice between these algorithm depends on the type of WSN application.

VI. CONCLUSION

Reports of successful application of bio-inspired heuristic search algorithms, such as PSO and bacterial foraging algorithm, and the untapped potential of ABC for sensor localization have inspired the research presented in this paper. WSN localization, a problem that has been formulated as an optimization problem, has been approached through the nature-inspired ABC algorithm here. A brief introduction to the localization problem has been provided. The ABC algorithm has been outlined. ABC-based approach to multistage localization of sensor nodes in a WSN has been detailed. Results of multistage localization have been presented and discussed briefly. The results have been compared with those of PSO-based iterative localization presented in earlier literature.

Statistical summary of the results shows that the ABC algorithm results in more accurate localization than PSO does. The results also show that PSO converges faster. This is a trade-off issue. It may be noted that localization is a one-time exercise in WSNs having stationary sensor nodes. In applications, such as surveillance and target tracking, accurate localization is desired. In such applications, the ABC is a suitable approach to sensor localization. On the contrary, in time-sensitive WSN applications, quick localization is crucial to the sensing mission. PSO is more suitable approach to localization in such applications. WSN size is another important factor to consider in making a choice between PSO and ABC. In the case of a WSN having thousands of nodes, multistage localization based on the ABC algorithm results in cascaded delays. On the other hand, PSO does the job quicker. Lastly, in WSNs having mobile nodes, localization is a repetitive exercise. The ABC is not an attractive approach in such WSNS due to its slower convergence. In summary, though the ABC algorithm can result in accurate localization, it comes with its own undesirable properties. Thus, it suits only certain limited class of WSNs.

The research presented here can be extended in many possible directions. There have been many reports on localization using a single mobile anchor. Finding an optimal path for the mobile anchor is an optimization problem as well. Algorithms, such as PSO and ABC can be used to accomplish localization through a single mobile anchor. Another direction for future research can be the hybridization of ABC in localization of sensor nodes for higher resource efficiency. This research may also be extended in the direction of developing quicker variants of the ABC algorithm, and applying the canonical or modified ABC algorithm for localization and other open optimization problems in WSNs or other domains. A comparative investigation of analytical methods and stochastic methods for localization is another possible direction for the extension of this study.

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