Performance Enhancement in Distributed Sensor Localization using Swarm Intelligence

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***Abstract*— Wireless Sensor Networks (WSNs) consist of distributed autonomous devices which sense the environmental or physical conditions cooperatively and pass the information through the network to a base station. Sensor Localization is a fundamental challenge in WSN. Location information of the node is critically important to detect an event or to route the packet via the network. In this paper localization is modeled as a multi dimensional optimization problem. This problem is solved using bio inspired algorithms, because of their quick convergence to quality solutions. Distributive localization is addressed using Particle Swarm Optimization (PSO) and Comprehensive Learning Particle Swarm Optimization (CLPSO). The performances of both algorithms are studied. The accuracy of both algorithms is analyzed using parameters such as number of nodes localized, computational time and localization error. Comparison of both the results is presented. A simulation was conducted for 100 target nodes and 20 beacon nodes, which resulted in CLPSO being 80.478% accurate, and PSO 61.48% accurate. The simulation results show that the PSO based localization is faster and CLPSO is more accurate.**

Keywords— Particle Swarm Optimization, Comprehensive Learning Particle Swarm Optimization, Localization, Wireless Sensor Network

I. INTRODUCTION

Sensor localization is a fundamental challenge in WSN. It is process of determining the physical coordinates of each individual sensor node in a WSN. Localization is straightforward when the network size is small, the area to be monitored is human-accessible, each node can easily be deployed manually, and the locations of each node can be registered during deployment. However, localization is more complex when manual deployment is infeasible or impossible to achieve i.e. the area of deployment is not human-accessible and/or there are many nodes in the network. In such a situation, then nodes are usually deployed by a vehicle, which is generally assumed to be an airplane or helicopter. An example, where this is necessary is in a forest fire detection system where nodes will be deployed by a plane.

The aim of this paper is to achieve efficient localization using a bio-inspired approach. Computational Intelligence (CI) provides an adaptive mechanism that exhibits intelligent behavior in complex and dynamic environments. This CI approach has been chosen for localization because it is flexible, gives optimal results and requires less memory when compared to other approaches.

In this paper localization is addressed as a multi dimensional optimization problem. The swarm intelligence techniques: Particle Swarm Optimization (PSO) and Comprehensive Learning Particle Swarm Optimization (CLPSO) are compared to determine which algorithm is better for solving the localization problem. A performance study of PSO and CLPSO based localization was undergone, using the parameters such as number of nodes localized, computational time and computational accuracy. It was observed that PSO was found to converge into a result faster compared to CLPSO, however CLPSO gives more accurate result. Considering the fact that, "Localization is a one-time optimization process in which solution quality is more important than fast convergence"[2]. We conclude that CLPSO is, currently, the optimal algorithm for the purpose of localization in more complex WSN deployment circumstances.

The rest of the paper is organized as follows. Brief information on similar approaches, in the literature, are presented in Section II. The algorithms considered for the localization problem are described in Section III. The localization approach is presented in Section IV. Discussion on simulation results is done in Section V. Finally, conclusion and future work in Section VI.

II. RELATED WORK

A survey on localization systems is described in [1]. In [2] issues in WSNs are formulated as multidimensional optimization problems, and are approached through bio-inspired techniques and a brief survey on PSO is also given. In this paper, swarm intelligence technique is used to solve the sensor localization problem.WSN localization is treated as a multidimensional optimization problem and PSO is proposed for centralized localization of WSN nodes in [3][4]. A centralized approach is used to solve the problem, where each node relays its connection statistics to a centralized authority which then computes the global solution. A two-phase centralized localization scheme which uses the approaches of simulated annealing and a genetic algorithm (GA), separately, is presented in [5]. A centralized localization method that uses simulated annealing and genetic algorithms, in combination, is proposed in [6]. However, a

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TABLE 1: Parameters choosen for both PSO and CLPSO based localization

Parameters	*Case Study 1: PSO based localization*	*Case Study 2: CLPSO based localization*
Accelaration Constants	*C1=2, C2=2*	*C1=1.49445 ,C2=1.49445*
Velocity of particle	*Vmax = Xmax Vmin = −Vmax*	Vmax = 10, Vmin = −10
Population size, Ps	*30*	
Number of iterations, Kmax	*200*	
dimesion, d	*2*	
Inertia weight,W	*linearly decreases in each iteration form 0.9 to 0.4*	
Particle boundary	*Xmin=Ymin=0, Xmax=Ymax=255*	

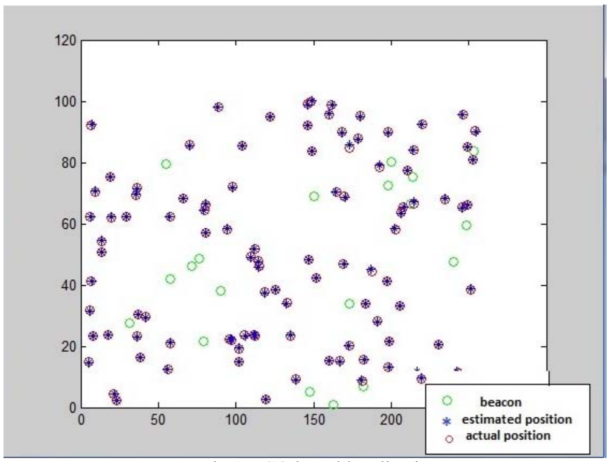

Fig 1. PSO based localization

main disadvantage of the centralized approach is that it scales poorly according to the size of the network.

An efficient localization system that extends GPS capabilities to non-GPS nodes in an ad hoc network is proposed in [7]. An investigation on distributed localization using Particle Swarm Optimization (PSO) and bacterial foraging algorithm (BFA) is presented in [8] . The distributed algorithm has much better scaling properties than a centralized solution and a lower communication cost, because the nodes are not required to relay information. Therefore, distributed solutions are more attractive for large networks containing thousands of nodes. So in the proposed system iterative distributed localization approach is used for sensor localization.Real-time results were compared from a PSO-beaconless algorithm and a Gauss-Newton algorithm [9]. It is observed that PSO has more localization accuracy than Gauss-Newton algorithm. Joining the search for the optimal localization algorithm, we compared the localization accuracy of PSO algorithms to CLPSO algorithms.

III. SWARM INTELLIGNCE TECHNIQUES

PSO consists of a swarm (population) of s particles, each one of them is a candidate solution. These particles search for a global solution in n dimensional space, n is the number of parameters to be optimized. Each particle has a position

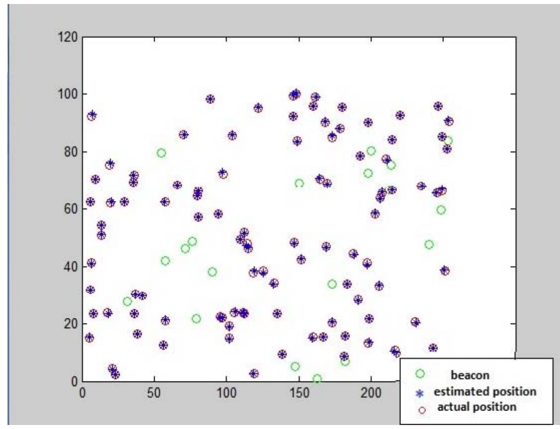

Fig 2. CLPSO based localization

represented by X_{id} and with a velocity V_{id} where i ranges from $1 \le i \le s$ and d ranges from $1 \le d \le n$. Each particle in the swarm is evaluated by an objective function $f(x_1, x_2,...,x_n)$. The fitness of a particle is determined from its position in the search space. The cost of a particle closer to the global solution is lower than that of a particle that is farther. Alternately, the fitness of a particle closer to the global solution is higher than that of a particle that is farther. PSO tries to minimize or maximize the fitness function. The fitness function is chosen based on the problem to be solved. In each iteration, the velocity and position of all the particles is updated to acquire a higher fitness. Each particle has its best value called $Pbest_{id}$. The

global best value is *Gbest*. At each iteration, *k* velocity V_{id} and position X_{id} of the particle is updated using the formula [2]

$$V_{id}(k) = wV_{id}(k-1) + c_1 r_{1id}(k)(Xpbest_{id} - X_{id}) + c_2 r_{2id}(k(Xgbest_d - X_{id}) \quad (1)$$

$$X_{id}(k) = X_{id}(k-1) + V_{id}(k) \quad (2)$$

Here, r1 and r2 are the random numbers with a uniform distribution in the range [0, 1]. Velocity update is dependent on three components of acceleration. w is the inertia of the particle which changes linearly in each iteration 0.2 ⩽ w ⩽ 0.9. Psuedocode for PSO is given in [9]. CLPSO Learning Strategy is explained in [15]. In this, position and velocity is calculated by by equation (3) and (4).

$$V_i^d = w \times V_i^d + c \times rand_i^d \times (pbest^d_{f_i(d)} - X_i^d) \quad (3)$$

$$X_i^d = X_i^d + V_i^d \quad (4)$$

Here *fi = [fi(1), fi(2), ...fi(D)]* denotes a set of particle indices with respect to each dimension of the particle i.fi(d) represents a comprehensive exemplar with each dimension composed of the value from the corresponding dimension of the pbest of particle *pbestfi.* These indices take the value *i* itself with the

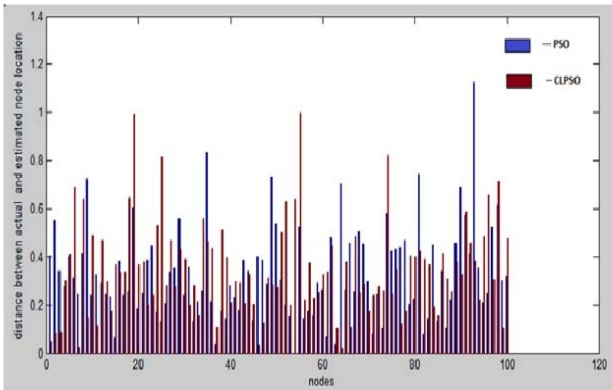

Fig 3. Distance between actual position and estimated position for both PSO and CLPSO

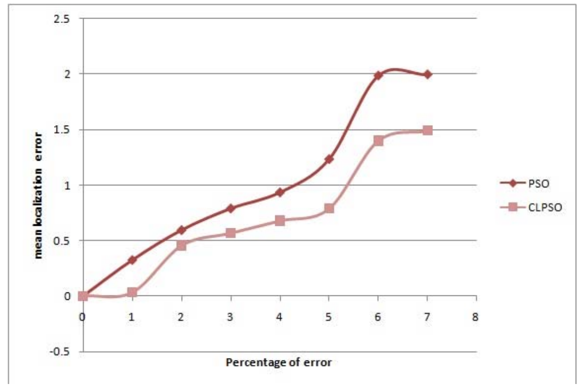

Fig 4. For increasing percentage of error the error rate is observed

probability *Pci*, referred to as the learning probability, which takes different values with respect to different particles. For each particle i a random number is generated. If this random number is greater than *Pci*, the corresponding dimension of particle i will learn from its own pbest, otherwise it will learn from the *pbest* of another randomly chosen particle. Tournament selection with size 2 is used to choose the index *fi(d).* To ensure that a particle learns from good exemplars and to minimize the time wasted on poor directions, we allow each particle to learn from the exemplars until [12] such particle stop to improve for a certain number of generations, called the refreshing gap m. After this refreshing graph *fi = [fi(1), fi(2), ...fi(D)]* is reassigned.

VI. LOCALIZATION ALGORITHM

The main aim of node localization is to estimate the position of as many N dumb nodes, as possible, when N dumb nodes and M beacon nodes are deployed in the field. Node localization is viewed as an optimization problem. In this algorithm, we are estimating the position by using bio-inspired algorithms CLPSO and PSO. The following assumptions are made for this algorithm This localization algorithm makes use of beacon nodes. The node deployment is assumed to be achieved by means of an autonomous or human-controlled vehicle. Lastly, the field over which the WSN is laid is assumed to be a forest and this assumption is made because a forest is one of the most challenging environments for a WSN.

Approach for node localization is as follows:

1) There are *N* dumb nodes and M beacon nodes who know their own physical coordinates in the field and both nodes *N* and *M* have transmission range, *r*.

2) Each node checks whether there are 3 or more non-collinear beacons in range. If there are 3 or more beacons in range, then that node will compute its distance from itself and those beacon nodes.

3)A node calculates its distance from a beacon node i using *dnew = di + ni* where ni is the gaussian additive noise while determing the distance. The distance di is calculated by equation (5).

$$d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} \quad (5)$$

Here *(x,y)* is the coordinate of the localizable node and (x_i,y_i) is the coordinate of the beacon node. The measurement noise ni has a random value uniformly distributed in the range *di±di(Pn/100).* It is clear that the result of localization depends on the value of *Pn*, the percentage noise that affects distance.

4) Two case studies are conducted to localize the nodes, in the first case, each node will run PSO, and in the second case, each node will run CLPSO. Both cases will calculate the position of the node *(x, y).* Both PSO and CLPSO will try to minimize the optimization function (6), where $M \geq 3$ is the number of beacons in the transmission range of the node to be localized.

$$f(x,y) = \frac{1}{M}\sum_{i=1}^{M}(\sqrt{(x - xi)^2 - (y - yi)^2} - dnew)^2 \quad (6)$$

5) PSO and CLPSO search for the best (x, y) value in the 2D space.

6) After localizing, the maximum number of nodes and the localization error is computed as equation (7) where (x_i,y_i) is the actual position of the node and (*xnew, ynew)* is the position estimated by PSO and CLPSO. L is the total number of nodes localized.

7) Repeat the steps from 2 to 6 until all the nodes are localized or the maximum number of nodes are localized. The performance of this localization algorithm can be determined from three parameters the number of non-localizable, N_L nodes where $N_L = N - L.$, localization error, E_r and accuracy of the algorithm which is calculated later in this paper. As the values of N_L and E_r decrease the performance of the algorithm increases. As number of iterations increase more and more nodes are localized. At the end of each iteration, these localized nodes become designated beacon nodes which help to localize even more nodes.

V.DISCUSSION AND RESULT

In the CLPSO and PSO based localization, it was observed that as the number of iteration increases, the number of nodes localized also increases. Table I shows the parameters chosen for both the case study. The Table II shows the average error and time required for both CLPSO and PSO. Each recorded trial is the average of 50 trials. The location estimated by PSO and CLPSO are shown in Fig1 and Fig2. The graph in Fig 3 gives the distances between the actual and

TABLE II: RESULTS OBTAINED FOR LOCALIZATION BOTH PSO CLPSO FOR VARYING NUMBER OF BEACONS

PSO				*CLPSO*			
Number of beacons=6		*Number of beacons=8*		*Number of beacons=6*		*Number of beacons=8*	
avg error(m)	*avg time(s)*	*avg error(m)*	*avg time(s)*	*avg error(m)*	*avg time(s)*	*avg error(m)*	*avg time(s)*
0.6472	*36.0360*	*0.5486*	*73.8721*	*0.3173*	*574.5513*	*0.0551*	*975.0115*

TABLE IIRESULT OBTAINED FOR PSO AND CLPSO LOCALIZATION EACH TRIAL IS DONE FOR 50 RUNS AND THE CORRESPOINDING VALUES ARE AVERAGED HERE Er IS THE AVERAGE ERROR, L IS THE NUMBER OF NODES LOCALIZED AND CT IS THE COMPUTATIONAL TIME REQUIRED

		PSO				CLPSO		
		Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 1	Iteration 2	Iteration 3
Trial 1	L	73	96	99	100	73	98	100
	Er	1.1843	1.4892	1.3164	0.5869	0.3269	0.4980	0.3031
	Ct	7.1794	16.5233	26.1706	9.3654	228.0498	458.7456	783.1441
Trial 2	L	90	99	100		90	99	100
	Er	0.1370	1.1326	0.1370		0.4929	0.3334	0.0639
	Ct	8.7894	18.3703	3.7326		352.6139	517.1685	294.5091
Trial 2	L	73	99	100		74	99	100
	Er	0.4314	0.6702	0.4314		0.2928	0.4171	0.21881
	Ct	7.0384	16.5746	26.1756		228.0498	358.7456	793.1441

the estimated location. From the Table II CLPSO is more accurate than PSO since CLPSO's average error is less for all cases when compared with PSO. It is also observed that as the percentage noise increases the average error value also increases for both CLPSO and PSO. In Table II, the maximum number of beacons which can be used for localizing a node is made as 6 in one case and 8 in another case. It was found that 8 beacon nodes can more accurately localize a node than 6 beacon nodes, but take a longer time to do so. From all these results it is evident that CLPSO is having more localization accuracy than PSO.

VI. CONCLUSION AND FUTURE WORK

Localization is viewed as a multidimensional optimization problem which has been resolved by bio inspired algorithms PSO and CLPSO in this paper. This localization approach aims to be more energy efficient than centralized approaches, making it an optimum choice when putting together a WSN. In distributed localization, the number of transmissions to the base station is less so energy of the WSN can be conserved. The two bio-inspired algorithms are outlined and the results are compared by measuring the parameters computational time, computational accuracy and number of nodes localized. These results are statistically represented. It was observed that PSO converges in to a result more quickly since computational time required for PSO is less than CLPSO. However, CLPSO gives more accurate result since it localization error is much less compared to PSO. A choice between PSO and CLPSO is influenced by constraints such as the memory and computational resources of the node available, and how accurate and quick.

The research can be extended in several directions. If the beacons are mobile, then a higher number of nodes can be localized. With the help of one mobile beacon node we can localize all the nodes in the field.. A study on the error propagation in the proposed localization approach could be conducted. Thirdly, CLPSO and PSO could be used for a centralized localization and compared with the results of the distributive localization.

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