A Swarm Intelligence Based Distributed Localization Technique for Wireless Sensor Network

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ABSTRACT

Wireless sensor network (WSN) refers to a group of spatially dispersed and dedicated sensors for monitoring and recording the physical conditions of the environment and organizing the collected data at a central location. Sensor Localization is a fundamental challenge in WSN. In this paper localization is modeled as a multi dimensional optimization problem. A comparison study of energy of processing and transmission in a wireless node is done, main inference made is that transmission process consumes more than processing. An energy efficient distributed localization technique is proposed. Distributive localization is addressed using swarm techniques Particle Swarm Optimization (PSO) and Comprehensive Learning Particle Swarm Optimization (CLPSO) because of their quick convergence to quality solutions. 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. A simulation was conducted for 100 target nodes and 20 beacon nodes, the results show that the PSO based localization is faster and CLPSO is more accurate.

Categories and Subject Descriptors

C.2.1 [Computer-Communication Networks]: Network Architecture and Design—Wireless communication; G.1.6 [Numerical Analysis]: Optimization —Global Optimization; G.1.3 [Numerical Analysis]: Numerical Linear Algebra—Error Analysis; I.6.6 [Simulation and Modeling]: Simulation Output Analysis. C.4 [Performance of Systems]

General Terms

Algorithm, Performance, Experimentation

Keywords

Wireless Sensor Networks (WSN), Particle Swarm Optimization (PSO) , Comprehensive Learning Particle Swarm Optimization (CLPSO), Localization

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1. INTRODUCTION

A wireless sensor network (WSN) consists of distributed autonomous devices which senses the environmental or physical conditions cooperatively and passes the information through the network to the base station. Each sensor node has a CPU, battery supply, limited number of sensors and a radio transceiver for communication [1]. Each sensor node has onboard radio which is used to send the collected data to the base station either directly or via multiple hops. The main Problems in WSN are scale and density of deployment, environmental uncertainties and constraints in energy, memory, bandwidth and computing resource.

Sensor localization is a fundamental challenge in WSN. It is process of determining the physical coordinates of individual the sensor node in 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. A Localization system are divided in to three phases [1]

- Distance/angle estimation: This is used to estimate the distance or angle between two nodes and this information is used by other components in the localization system for further use. Fig 1 as [7] shows the distance/angle estimation in WSN.
- Position computation: This component is used for computing a node's position based on available information distances/ angles computed by other component and positions of beacon nodes.
- Localization algorithm: This is the main component of a localization system. It determines how the available information will be manipulated in order to make most or all of the nodes of a WSN to estimate their physical coordinate.

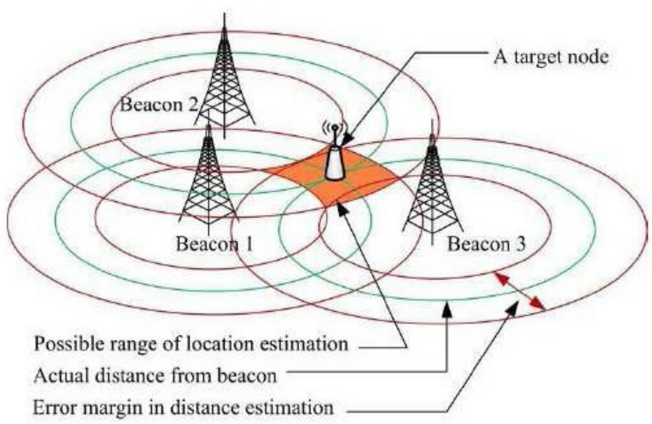

Figure 1: Distance estimation in WSN

In this paper the energy required for transmission and processing is calculated for wireless node, main inference made is than transmission takes more energy when compared to processing. An energy efficient localization approach is proposed where more node level processing is done than transmission. 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.

2. RELATED WORK

A survey on localization system is described in [1]. Computational Intelligence (CI) provides adaptive mechanism that exhibit intelligent behavior in complex and dynamic environment. In [7] 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 the current research 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]. PSO is proposed for centralized localization of WSN nodes in [12]. A position estimation approach in a sensor network using convex optimization is presented in [2]. In this paper 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 approaches simulated annealing and GA is presented in [11]. A centralized localization method that uses a combination of GA and simulated annealing algorithm proposed in [14]. The centralized approach scales poorly with 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 [13]. 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. The real-time results comparison of PSO-beaconless algorithm with Gauss-Newton algorithm is presented in [4]. It is observed that PSO has more localization accuracy than Gauss-Newton algorithm. Here, we compared localization accuracy of PSO algorithms is compared with CLPSO.

3. Comparison study on Energy consumption of transmission and processing in wireless node

The Energy for processing and transmission in MICAZ mote is practically calculated. To calculate the power consumed by the mote for processing. Using Nesc Programming processing is done in the mote for a particular time unit T. Initial power *Ei* and power in the battery after processing *Ep* is calculated. Energy required for processing, Er is calculated by (1)

$$Er = Ei - Ep \qquad (1)$$

To calculate the power consumed for transmitting the packet by the radio CC2420. Using NesC programming the Micaz mote programmed for broadcasting packets using the repeat timer. In the Xsniffer the transmitted data is logged . From this data the power for one transmission is calculated. Table 2 below gives the energy required for both transmission and processing. The Figure 2 is the graph which shows the comparison of both transmission and processing power. From the study it became evident that if more nod level processing is done then less energy will be consumed. An energy efficient localization approach is proposed.

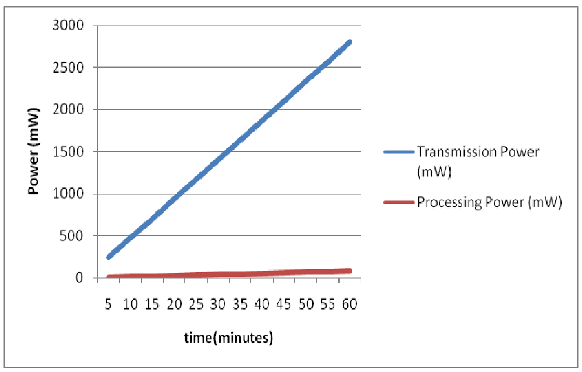

Figure 2: Comparison of energy consumption of Transmission and processing

4. Swarm Intelligence Techniques

In this paper localization problem is solved using two swarm intelligence techniques Particle Swarm Optimization (PSO) and Comprehensive Learning Particle Swarm Optimization (CLPSO). The description of PSO an CLPSO is given below.

4.1 Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO) is a population based stochastic optimization technique which shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA) [9]. 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 represented by X_{id} and with a velocity V_{id} where i ranges from $1 \leq i \leq s$ and d ranges from $1 \leq d \leq n$. 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].

$$V_{id}(k) = wV_{id}(k-1) + c_1 r_{1id}(k)\left(X_{pbestid} - X_{id}\right)$$
$$+c_2 r_{2id}(k)\left(X_{gbestid} - X_{id}\right) \qquad (2)$$

$$X_{id}(k) = X_{id}(k-1) + V_{id}(k) \qquad (3)$$

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 accelaration.*w* is the inertia of the particle which changes linearly in each iteration $0.2 \leq w \leq 0.9$. Pseudo code for PSO is given in [8].

4.2 Comprehensive Particle Swarm Optimization (CLPSO)

A CLPSO Learning Strategy is explained in [10].

$$V_i^d = w * V_i^d + c * rand_i^d * \left(Pbest_{fi(d)}^d - X_i^d\right) \qquad (4)$$

$$X_i^d = X_i^d + V_i^d \qquad (5)$$

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 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 [15] 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. The pseudo code of CLPSO is presented in Algorithm 1 and Algorithm 2 is procedure to select exembler in for a particle.

Algorithm 1 Comprehensive Learning PSO

Intialize position X,Velocity V, $Pbest$ and $Gbest$
Intialze $w_0 = 0.9$, $w_1 = 0.4$, $c = 1.49445$ and $m = 7$
while $K < K_{max}$ **do**
$w_(k) = w_0 \times \frac{(w_0 - w_1 \times k)}{max_{gen}}$
for $i = 0 : s$ do **do**
if $(flag_i \geq m)$ **then**
call Procedure select exembler()
$flag = 0$
end if
for each dimension d **do**
compute V_{id} using (3.3)
restrict V_{id}:$V_{min} \leq V_{id} \leq V_{max}$
compute X_{id} using (3.4)
end for
if $(x \in [X_{min}, X_{xmax}])$ **then**
if $f(X_i) \leq f(Xpbest_i)$ then **then**
for each dimension d do **do**
$Xpbest_{id} = X_{id}$
end for
$flag_i = 0$
end if
if $f(X_i) \leq f(Xgbest)$ then **then**
for each dimension d do **do**
$Xgbest_d = X_{id}$
end for
end if
else
$flag_i = flag_i + 1$
end if
end for
end while

Algorithm 2 Procedure for selection for exembler for particle i

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Intialize $pci = 0.05 + 0.45 * \frac{exp(\frac{10(i-1)}{s-1})-1}{exp(10)-1}$
for each dimension d **do**
if $(rand < pci)$ **then**
$f1_i^d = \lceil rand1_i^d * s \rceil$
$f2_i^d = \lceil rand2_i^d * s \rceil$
if $f(pbest_{f1_i^d}) > f(pbest_{f2_i^d})$ **then**
$f_i^d = f1_i^d$
else
$f_i^d = f2_i^d$
end if
else
$f_i^d = i$
end if
end for

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5. 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 (6).

$$d = \sqrt{(x - xi)^2 - (y - yi)^2} \qquad (6)$$

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 as equation (7), where $M \geq 3$ is the number of beacons in the transmission range of the node to be localized.

$$f(x,y) = \frac{1}{M}\sum_{i=1}^{M}(\sqrt{(x-xi)^2 - (y-yi)^2} - dnew)^2 \qquad (7)$$

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 (8)

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.

$$Er = \frac{1}{L}\sum_{i=1}^{L}((xi - x_{new})^2 + (yi - y_{new})^2) \qquad (8)$$

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. In Figure 3. flow chart for Localization approach is presented.

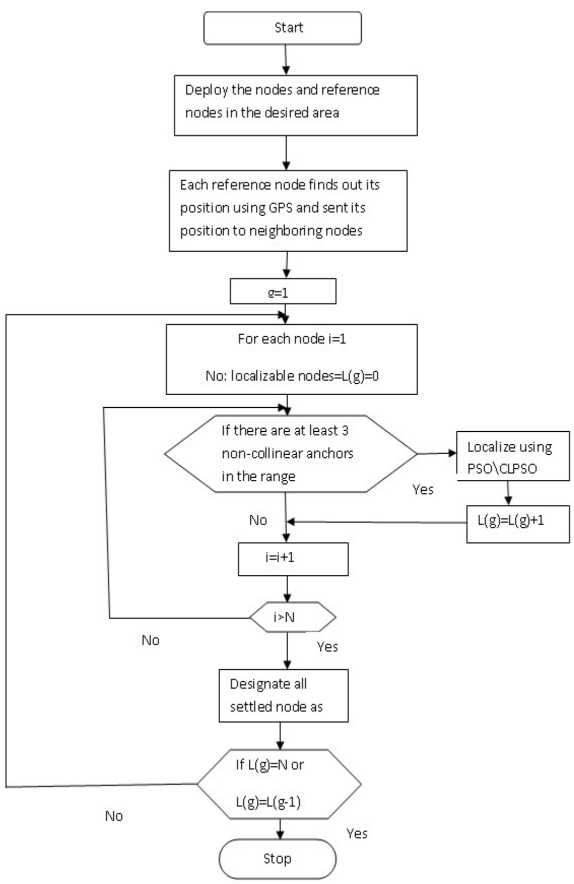

Figure 3: Flow chart of localization approach

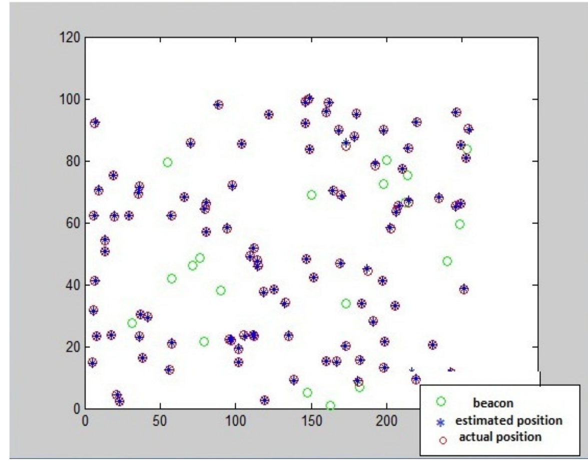

Figure 4. PSO based Localization

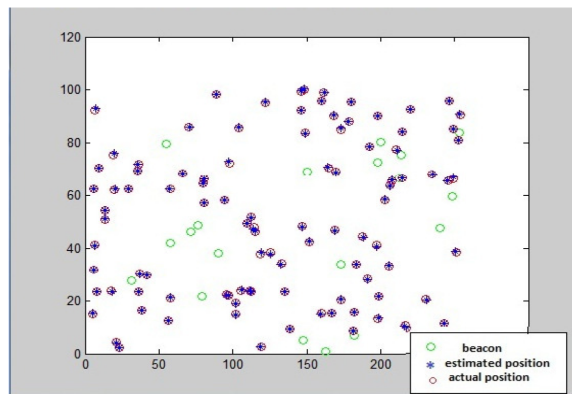

Figure 5: CLPSO based localization

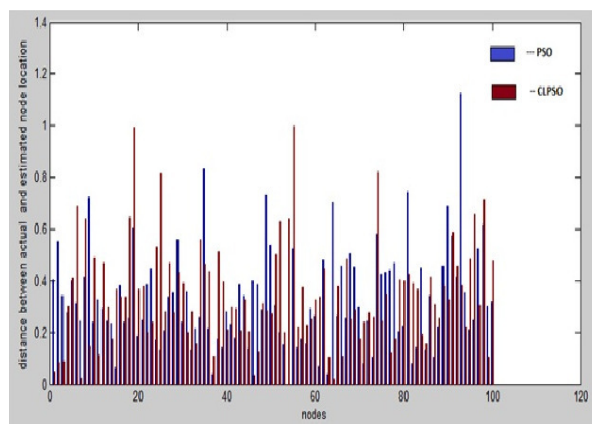

Figure 6: Distance between actual position and estimated position for CLPSO and PSO

6. Discussion and Result

The energy comparison of transmission and processing in wireless probe is calculated practically. The main observation made is that transmission energy is high when compared to processing. So to

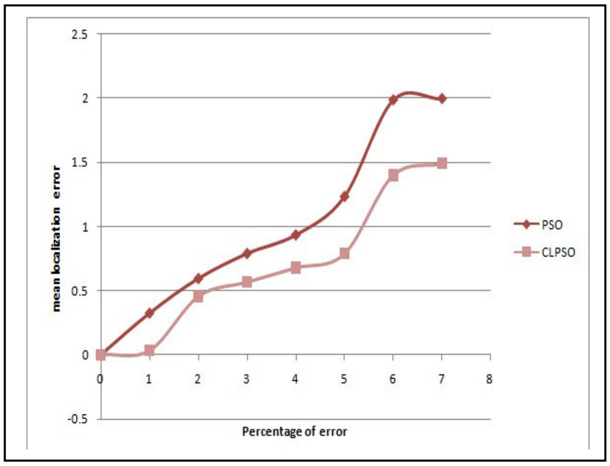

Figure 7: For increasing percentage of error the error rate is observed for PSO and CLPSO

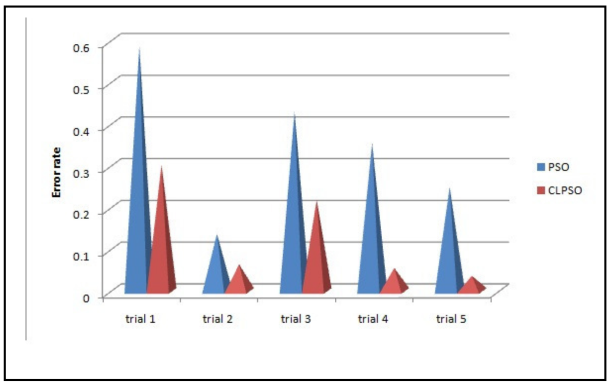

Figure 8: For each trial the error rate of PSO and CLPSO is determined.

design an energy efficient localization number of transmissions must be reduced and more node level processing must be done. In the CLPSO and PSO based localization, it was observed that as the number of iteration increases, the number of nodes localized also increases. The Table I 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 Figure 4 and Figure 5. The graph in Figure 6 gives the distances between the actual and 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. The computational time required for localization is more for CLPSO than for PSO.

It is also observed that as the percentage noise increases the average error value also increases for both CLPSO and PSO. In Table I, 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.

7. CONCLUSION

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. From the Energy study it became evident that transmission take high energy 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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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 III: RESULT 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