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Biologically Inspired Algorithms Case Study for Node Localization in Wireless Sensor Networks using LabVIEW.

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ABSTRACT

Nature is of course a great source of inspiration for solving complex problems in the electronics era since it exhibits exceptionally diverse, dynamic and complex phenomenon. Wireless sensor networks (WSN) have become popular in many applications area including environmental monitoring, military and medical industries. This paper deals about how the behavioural pattern of natural living organism could be used to make algorithms for optimization techniques. In WSN the sensors are randomly deployed in the sensor field and hence estimation of the localization of each deployed node has drawn more attention by the recent researchers, It's a unique problem to identify and maximizing the coverage where the sensors need to be placed in a position so that the sensing capability of the network is fully utilized to ensure high quality of service. In order to keep the cost of sensor networks to a minimum, the use of additional hardware like global positioning system (GPS) can be avoided by the use of effective algorithms that can be used for the same. In this paper we attempted to use and compare the performance of Particle Swarm Optimization (PSO) and Shuffled frog leaping (SFLA) to estimate the optimal location of randomly deployed sensors. The results were compared and published for the usefulness of further research.

Keywords: WSN, SFLA, PSO, localization, RSSI, ToA

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INTRODUCTION

Wireless Sensor Networks are distributed self-directed contain nodes which can senses and update the data's to the base station which are discussed in article [1].WSN technology becoming popular in all areas of applications including military, medical, process and electronic industries due to its easy implementation and maintenance. The interest of research is to analyse the possibility of utilising it for process industries and hazard location is interest of research; however the issues with WSN are the deployment of the nodes, localisation and energy aware clustering and an optimized solution required to do the same. Generally localization in WSN is done by equipping a Global positioning system (GPS) with each sensor node is to be done; however equipping a GPS with each sensor node is cost wise more expensive solution. Therefore an alternate solution need to be found to address the localization issues, which comes out in the form of utilising the optimization algorithms for localization. The conventional optimization techniques are useful only for less number of nodes and requires more computational efforts with respect to the problem size .Hence an optimization method is required to overcome all these issues and currently our researchers has developed so many algorithms particularly based on the inspired characters from the natural living things. These Bio-inspired algorithms methods of optimization are computationally efficient compared to the conventional analytical methods; mainly Particle Swarm Optimization (PSO) and Shuffled Frog leaping algorithm (SFLA) are popular multi-dimensional optimization techniques. The features of these PSO, SFLA and FFA are easy to implement, comparatively more accurate solutions, computational efficiency and fast convergence.

A WSN consists of *N number of* nodes and the communication range between them is r, the nodes are distributed in the sensing field. The WSN is represented as the Euclidean graph $G = (X, Y)$, where $X= \{a1, a2. . .an\}$ is the set of sensor nodes. $i, j \in Y$ij the distance between ai and $Xj$is$dij \leq r$. Unknown nodes are the set V of non-beacon nodes which location to be determined. Settled nodes are the set S of nodes that managed to estimate their positions using the localization algorithm.

Given a WSN $G = (X,Y)$, and a set of beacon nodes B and their positions (xb, yb), for all $b \in B$, it is desired to find the position (xu, yu) of as many $u \in U$ as possible, transforming the unknown nodes into settled nodes S.

In the article [2] existing location awareness approaches is discussed, there is two techniques commonly employed, the first one is based on distance or angle measurement and second is combination of distance and angle. Received Signal Strength Indicator (RSSI) is the most popular method of measuring the node position by calculating the distance of nodes. Time of arrival (ToA) and Angle-of-Arrival (AoA), Triangulation and Maximum Likelihood (ML) estimation are the other methods. RSSI technique is based on the receiving power and attenuation of radio signal exponentially with the increase of distance. In RSSI the distance can be calculated based on the loss in power by comparing the theoretical model. Time based methods Time of Arrival (ToA) and estimates the distance by the difference of propagation time between two nodes with known velocity of signal propagation. Angle-of-Arrival (AoA) also known as Direction of Arrival (DoA) techniques calculates the position by geometric coordinates with the angle from where signals are received. As per as accuracy of determination is concerned ToA, and AoA methods are ahead RSSI, due to loss in radio signal amplitude by environmental factors. Triangulation technique is based on the direction measurement of the node instead of the distance measured in AoA systems. The node positions are determined by trigonometry laws of sinø and cosinø. Maximum Likelihood (ML) estimation calculates the position of a node by minimizing the differences between the measured distances and estimated distances. The localization in WSN is done in two phases, one is ranging phase and another one is estimation phase. The nodes estimates their distances from beacons (or settled nodes) using the signal propagation time or the strength of the received signal in the ranging phase. Due to noise accurate measurement of these parameters are not possible due to noise and hence the localisation algorithms uses these parameters may not be accurate. In the second phase, estimation of the position is carried out using the ranging information. This can be done either by traditional way of solving a set of simultaneous equations, or other way by using an optimization algorithm which minimizes the localization error.

In the localization algorithm which uses iteration method, the nodes which are settled serve as beacons and the process of localization is continued until either all nodes are settled, or with no more nodes can be localized.

In this paper we did performance study of two important bio-inspired optimization algorithms involved node localization in a WSN. The particle swarm optimization (PSO) discussed in article [3] and shuffled frog leaping algorithm (SFLA) which is detailed in article [4].Because of easiness in solving problem with high efficiency in multidimensional search nature these algorithms are popular in the recent day's research.

The paper is organized as follows: Part 2 discusses about the literature survey of previous research in WSN localization. Part 3 presents PSO and SFLA optimization algorithms used for localization in this study. Part 4 explains how the localization problem is approached using the above mentioned optimization methods. Part 5 is about results and discussion based on the simulation work done and Part 6 presents conclusions and future possible research path.

Review of Related Work

Article [5] is a survey of localization methods for WSNs using bio inspired algorithms. An efficient localization system that extends GPS capabilities to non-GPS nodes in an ad hoc network is proposed in [6] using particle swarm optimization. Article [7] is about using PSO and shuffled frog leaping algorithm in which anchors flood their location information to all nodes in the network and each dumb node estimates its location by trilateral method, also the localization accuracy is improved by measuring the distance between the neighbours. In article [9] the node localization is discussed using convex position estimation and then the semi-definite programming approach is further extended to non-convex inequality constraints in article [10]

WSN localization considered as a multidimensional optimization problem and evaluated though population-based techniques in recent days. The centralised localization techniques are discussed in article [11] and this approach requires a large number of beacons in order to localize all dumb nodes. In article [12] a genetic algorithm (GA) based node localization algorithm is presented which determines locations of all non-beacon nodes by using an estimate of their distances from all one-hop neighbours. Similarly in article [13] a two-phase centralized localization scheme that uses simulated annealing and GA is presented.

The advantage of distribute localization techniques over the centralised one is because of the complexity in nature and scalability issues present in centralised WSN techniques. The distributed localization algorithms will be developed and deployed on each individual sensor node instead of central base station adopted in centralised techniques. The target nodes localize based on distance measurement from the neighbouring beacons or already localised nodes. The case study done in this paper infers few features for in particular the localisation accuracy and the iterative method of localization ensures more number of nodes are localised in short span of time

Bio-Inspired Techniques – PSO and SFLA for WSN Localization

Natural living organism provides rich source of ideas for computer scientists. The bio-inspired algorithms offer better accuracy and modest computational time. PSO and SFLA and bio inspired algorithms are discussed in the following subsections.

Particle Swarm Optimization Algorithm (PSO)

Particle swarm optimization (PSO) is a computational method that optimizes problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. It is developed based on social behaviour of a flock of birds. PSO optimizes a problem by having a population of candidate solutions with particles, by using simple formulas moving these particles around in the search space over the particles positions and velocity. There have been many modifications since after its introduction [6], and many versions of PSO have been proposed and applied to solve optimization problems in diverse fields [14]. Similarly in article [15] the author discussed about Particle Sharing Based Particle Swarm Frog Leaping Hybrid Optimization Algorithm. In PSO the movement of each particle is influenced by its local best known position, which will be considered as better positions found by other particles. As mentioned earlier the two mathematical formulas are used to resolve the particle movements in the search space. The movements of the particles in the search space is guided by their own best known position and when improved positions are being discovered then these will come to guide the movements of the swarm. This process will be repeated until a satisfactory solution is obtained. The particles move around in an n-dimensional space to search the global solution, where n represents the number of parameters to be optimized, x and y coordinates of a nodes. The objective is to determine the fitness of the particle in the search space which is decided based its closeness to the global solutions. Now each particle i has a position Xi_d and moves with a velocity Vi_d, $1 \le i \le s$ and $1 \le d \le n$. The best particle which has highest fitness position in that particular iteration of the search is called $pbest_{id}$(local best), and $gbest_d$ (global best)is the maximum of $pbest_{id}$ of all particles in the iterative search which is the best possible solution. The velocity Vid and position Xid of each particle in k^{th} iteration is updated using equation (1) and (2).

$$Vid(k+1) = w.Vid(k) + C1.rand1.(Pbestid - Xid) + C2.rand2.(gbestd - Xid) \quad (1)$$

$$Xid(k+1) = Xid(k) + Vid(k+1) \quad (2)$$

Here, rand1 and rand2 are random numbers that range between 0 and 1 with a uniform distribution. The PSO algorithm will be written as follows

PSO Algorithms Pseudo Code

1: Initialize w, c1 and c2
2: Initialize maximum allowable iterations kmax
3: Initialize the target fitness fT
4: Initialize Xmin, Xmax, vmin and vmax
5: for each particle i do
6: for each dimension d do
7: Initialize Xid randomly: Xmin ≤ Xid ≤ Xmax
8: Initialize vid randomly: vmin ≤ vid ≤ vmax
9: end for
10: end for
11: Iteration k = 0
12: while (k ≤ kmax) AND (f (gbest) >fT) do
13: for each particle i do
14: Compute f (Xi)
15: if f (Xi) <f ($pbest_i$) then
16: for each dimension d do
17: $pbest_{id}$ = Xid
18: end for
19: end if
20: if f(Xi) < f(gbest) then
21: for each dimension d do
22: gbestd = Xid
23: end for
24: end if
25: end for
26: for each particle i do
27: for each dimension d do
28: Compute velocity vid(k + 1) using (1)
29: Restrict vid to Vmin ≤ Vid ≤ Vmax
30: Compute position Xid(k + 1) using (2)
31: Restrict Xid to Xmin ≤ Xid ≤ Xmax
32: end for
33: end for
34: k = k + 1
35: end while

Shuffled Frog Leaping Algorithm (SFLA)

Shuffled frog leaping algorithm is swarm intelligence based biological evolution algorithm. The algorithm simulates a group of frogs in which each frog represents a set of feasible solutions. The different memeplexes are assumed as different culture of frogs which are located at different places in the solution space In article [16]in the execution of the algorithm, In order to form a group "F" frogs are generated and for a N-dimensional optimization problem, frog "i" of the group is represented asXi = (x1i; x2i; ...;xNi).Then based on the fitness values the individual frogs in the group are arranged in descending order, to determine Px the global best solution. The group is divided into m ethnic groups and each ethnic group includes n frogs by satisfying the relation F = m _ n. The ethnic group divided such that teach group will be in to their sub group like first group in to first sub group and second will be in second sub group and so on similarly frog m into sub-group m, frog m + 1 into the first sub-group again and so on, until all the frogs are divided the objective is to find the best frog in each sub-group, denoted by *Pb* and worst frog *Pw* correspondingly,. The iterative formulas will be written as equation (3) and (4):

$$D = rand() * (Pb - Pw) \quad (3)$$
$$Pnew_w = Pw + Di; \quad -Dmax \geq Di \geq Dmax \quad (4)$$

Where

- rand () represents a random number between 0 and 1,
- Pb denotes the position of the best frog,
- Pw denotes the position of the worst frog,
- D represents the distance moved by the worst frog,
- Pnew_w is the better position of the frog,
- Dmax represents the step length of frog leaping.

In the SFLA algorithm execution, if the updated *Pnew_w* is in the feasible solution space m then the corresponding fitness value of *Pnew_w* will be calculated. If the resultant fitness value of *Pnew_w* is worse than the corresponding fitness value of *Pw*, then *Pw* will replace *Pb* in equation (3) and re-update *Pnew_w*. If there is still no improvement, then randomly generate a new frog to replace *Pw;* repeat the update process until satisfying stop conditions

SFLA Algorithms steps

(1) Initialize groups and parameters such as group total number of particles N, total number of frogs N1, number of sub-groups m, number of frogs in each sub-group and the updates within the sub group
(2) Analyze the initial fitness values of the particles and save the initial best positions and best fitness values, then sort all N particles in ascending order as per the fitness values;
(3) According to the sub group division rule sort the N frogs in ascending order and divide them into sub-groups.
(4) Find out the best fitness individual Pb and the worst fitness individual Pwof each subgroup in frog group and also the group best individual Px
(5) Progress the worst solution within a specified number of iterations based on equations (3) and (4).
(6) According to the fitness value, arrange particles of the group in ascending order and re-mix the particles to form a new group.
(7) If stop conditions are satisfied (the number of iterations exceeds the maximum allowable number of iterations or the optimal solution is obtained), the search stops, and output the position and fitness value of the first particle of the group; otherwise, return to step (3) to continue the search.

Problem Statement and Methodology

In WSN node localization the objective is to perform estimation of coordinates of the distributed nodes to know their initial locations. If there is a maximum of N target nodes then using M stationary beacons whose know their locations then the location of unknown nodes will be determined. The following study approach is formulated for the localization of the same;

1) Initialize the sensors randomly
2) Initialize the beacons randomly
3) Calculate real distance ie the actual distance between the beacon and each deployed sensor nodes

4) Assign measured distance ie the distance obtained by the beacons using ranging techniques. This is done by adding noise to the real distance.
5) Find out how many sensors are within the transmission range of 3 or more beacons
6) For each sensor that can be localized for PSO and SFLA are applied to minimize the objective function which represents the error function given by the equation (5)

$$\sum_{i=1}^{n} ei = \sum_{i=1}^{n} \frac{(Ri - \sqrt{(xi - xm)^2 + (yi - ym)^2})^2}{Ri} \qquad (5)$$

Here Ri is the inexact ranging distance.

(xi, yi) is the corresponding beacon positions
(xm, ym) is the position occupied by the particle
"n" is the number of beacons having transmission coverage over that sensor

7) The algorithms return the closest values of the coordinates (xm, ym) such that error is minimized.
8) The algorithm is then applied to the next sensor in range
9) The localized sensors are removed from the sensor list and now act as beacons
10) The localization error is computed after all the Nl nodes estimate their coordinates, it is the mean of squares of distances between actual node locations (xi, yi) and the locations (ˆxi, ˆyi), i= 1, 2 ...Nl is determined by PSO and SFLA. This is computed as equation (6).

$$\mathrm{El} = 1/Nl \sum_{i=1}^{l} \left((\mathrm{xi} - \widetilde{xi})^2 \, (yi - \widetilde{yi})^2 \right) \qquad (6)$$

11) All the steps from 3 to 9 will be continued until either all unknown nodes get localized or no more nodes could be localized further. It is evident that the performance of the localization algorithm if observed from the values of N_{Nl} and El where N_{Nl} = N −Nl is the number of nodes that could not be localized. The lower values of N_{Nl} and El represent the better performance.

If the objective is to localize more number of nodes then the number of iterations steps, then the number of localized nodes increases. This increases the number of base references for already localized nodes. Firstly A node that localized using just three references in an iteration k may have more references in iteration k+1. Thus the chance of ambiguity is decreased. Secondly, the time required for localizing a node increases, if a node has more references in iteration k + 1 than in iteration k. The above issue is overridden in this performance study by limiting the maximum number of reference to six, which is arbitrarily chosen. The simulation is done using LabVIEW graphical user interface, the advantages of using LabVIEW can help for real time implementation in future scope of research.

Simulation is done in LabVIEW to understand the performance of WSN Localization. We chose 50 nodes as target to be localized and 10 beacons. The sensor field dimension is considered as 100×100 square units and the transmission radius of beacon r = 25 units. The same simulation settings in LabVIEW for both the performance studies are made same and the results are presented.

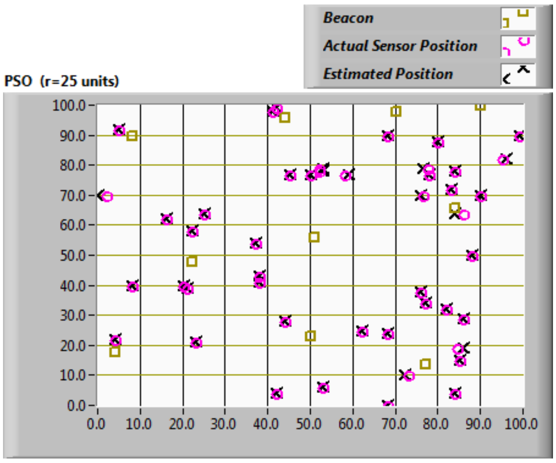
For all PSO and SFLA performance study, the parameters are: Population = 70, Iterations = 50, constants C1=c2=2, inertial weight w is decreased linearly from 0.9 in the first iteration to 0.9 to the last iteration. Particle position limits: Xmin=0 and Xmax=100.Total 30 trial experiments of SFLA based localization are conducted for Pn = 2 and Pn = 5. Average of total localization error El defined in (6) in each iteration in 25 runs is computed and the error is calculated.

DISCUSSION ON THE RESULTS

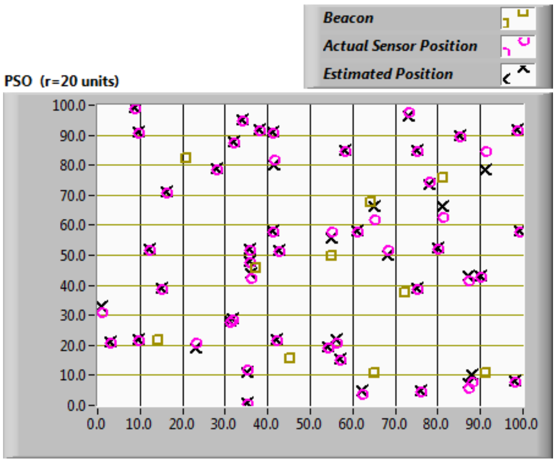
The two algorithms analysed here are stochastic and hence they do not produce the same solutions in all iterations though the initial deployment is same. That's why the results of multiple trial runs are averaged. In addition the initial deployment is random and hence the number of localizable nodes in each trial will not be same. This affects the total computing time.

The coordinates of the estimated and actual locations of nodes as well as the beacons by PSO and SFLA in a particular trial run are shown in Figure 1. The initial deployment of nodes and beacons for PSO and SFLA based localization is the same in a trial run. Table 1 gives the summary of the various parameters obtained from the result of PSO and SFLA based localization algorithms. The performance of all the three algorithms found fairly well in WSN localization. It has been observed that the localization accuracy is impacted by adding the Pn, percentage noise in distance measurement. It is also found that the average localization error in PSO and SFLA is reduced when Pn is changed from 5 to 2. The performance metric doublet (N_{Nl},El) for SFLA is less than that for PSO, indicating superior performance of SFLA. However, computing time required for SFLA is significantly more than that for PSO, which is a disadvantage of SFLA. Moreover, the memory required for SFLA is more than that for PSO and hence it gives room for a trade-off. The selection of these algorithms purely depends on the memory and computing resources and also how accurate the localization is expected to be and how quickly that should happen for the node localization.

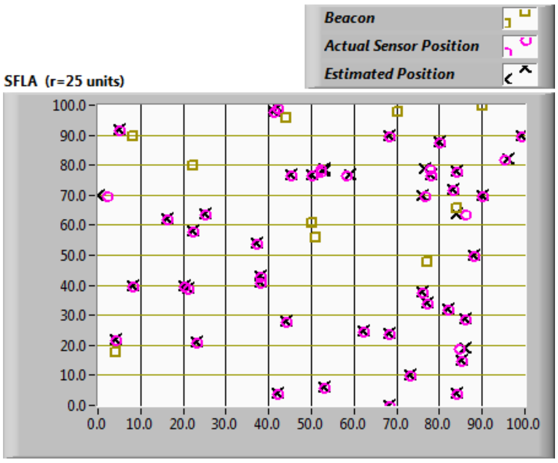
The effect of ranging distance error observations made in the first five trial runs out of the 50, are summarized in Table I. This table depicts increasing Nl, the number of localized nodes in each iteration. Table II shows the impact on the test results by varying the transmission radius. It is evident that the number of non-localized nodes increases when the transmission radius is made as 20 units from 25 units. It is also found that there is a correction of error due to flip of ambiguity from the Table I.



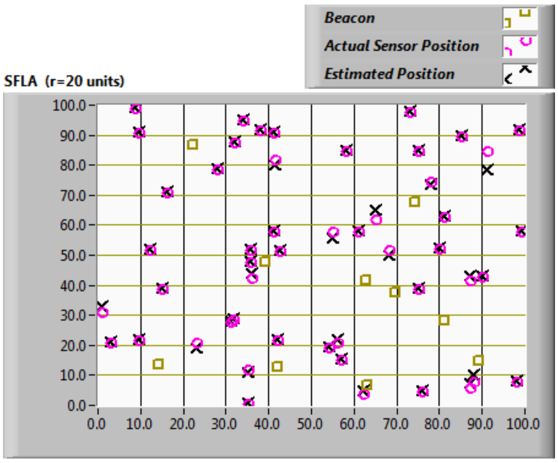
(a) Locations estimated by PSO r=25m



(a1) Locations estimated by PSO r=20m



(b) Locations estimated by SFLA r=25m



(b1) Locations estimated by SFLA r=25m

Figure 1: Result of trial run of PSO and SFLA algorithms for the same deployment with N=50; M=10; and the sensor field range is 100x100 square units

Table I: Effect of ranging distance error of SFLA, FFA and PSO

Major Parameters	SFLA		PSO	
	Pn=2%	Pn=5%	Pn=2%	Pn=5%
Avg. no of non-localized nodes(N_{NI})	0.37	1.22	0.61	1.96
Avg. time taken*(s)	418.1*	383.5*	110.9*	121.5*
Avg. localization error (El)	0.327	0.64	0.527	0.764

Table II: Effect of varying the transmission radius (r)

Major Parameters	SFLA		PSO	
Transmission radius (r)	20	25	20	25
Avg no of non-localized nodes	1.9	0.36	3.2	0.64
Avg. time taken*(s)	281.8*	583.5*	40.4*	111.5*

*All simulation are performed in the same computer

CONCLUSIONS

This paper has discussed PSO and SFLA bio-inspired algorithms to find out the localised nodes of a WSN in a scattered and iterative method. The localization problem is considered as a multidimensional optimization problem and solved by the above mentioned population-based optimization algorithms. From the results obtained it was found that SFLA offers less error value in comparison to the PSO but takes longer computational time to perform . We also ran the program with a smaller transmission radius and found that it leads to less number of nodes being localised. Although there is not vast difference in the errors offered by both the selection of what algorithms to use for localisation depends entirely on the hardware available to the user and the time constraints involved. This paper has also briefly presented a statistical summary of the results for comparison of PSO and SFLA. Both the algorithms are effective in their own way and can be further modified to suit the users need by changes in the program code to give even better results than what was obtained.

This work can be extended in many other directions, in a possible further study, all PSO and SFLA can be used in centralized localization method so that to compare the localisation methods of centralized and distributed techniques, which can lead to solve energy awareness issue in WSN.

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