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Heuristic Optimization Techniques For Node Localization In Wireless Sensor Networks

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Abstract: **-- Wireless sensor networks(WSN) has a wide range of applications in different domains such as environmental monitoring , disaster management ,target tracking, military affairs etc. 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.Node localization in Wireless Sensor Networks (WSNs), plays a critical role In this paper some popular bio inspired optimization method Hybrid PSOGA is compared with the recent optimization method known as Firefly algorithm. This paper conducts experimental simulation, comparison and evaluation work in the node localization using Firefly algorithm and Hybrid PSOGA by considering distance factor and improved objective function . Giving the distances between a sensor and a few of its 1-hop neighbors, the proposed algorithm can estimate the sensor positions. Simulation results show that the proposed method can achieve better results than those obtained from the HybridPSOGA.**

Keywords:**--Node localization,Geneticalgorithm,firefly algorithm, Swarm intelligent,**

I. INTRODUCTION

Wireless sensor networks(WSN) has a wide range of applications in different domains such as environmental monitoring ,disaster management ,target tracking,military affairs etc. Locating sensor nodes as accurate as possible is an important issue.Node localization in WSN is a two-phase process. The first phase is known as ranging phase where, nodes estimate their distances from their position to anchor nodes using the signal propagation time or the strength of the received signal. In the second phase, position estimation of the nodes is carried out using the ranginginformation. The localization error is minimized by using the optimization algorithm[3,10]. Consider a network with n target nodes and m anchor nodes.Assume that the anchor nodes coordinates are (xi,yi) where xi=[x1,x2,…..xm]yi=[y1,y2…,ym] and the location of target nodes are (xj,yj)where xj=[x1,x2,…xn] yj=[y1,y2,…yn]A node estimates its distance from a anchor as:

$$d_l = d_i + n_i$$

Where $d_i$is the actual distance. It is given as

$$d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} \qquad (3)$$

In second phase the objective function for the node localization problem can be framed as

$$(x, y) = \frac{1}{M}\sum_{i=0}^{M}\left(\sqrt{(x - x_i)^2 + (y - y_i)^2} - d_l\right)^2$$

where M ≥ 3 is the number of anchor nodes within the transmission radius of the target nodes.

II RELATED HEURISTIC OPTIMIZATION ALGORITHMS

A. Genetic Algorithm(GA): It is one of the evolutionary algorithm which was invented byJohn Holland in the early 1970's.GA through selection, crossover and mutation die out the low-fitness individuals and maintain high-fitness individualslike in the real nature.

B. Particle swarm optimization(PSO): It is a population-based stochastic searching technique developed by Kennedy and Eberhart (1995). Itcomes from the natural behavior of birds seeking for food. PSO applies the concept of social interaction to problem solving.It uses a number of agents (particles) that constitute a swarm moving around in the search space looking for the best solution.Each particle keeps track of its coordinates in the solution space which are associated with the best solution (fitness) that has achieved so far by that particle. This value is called personal best, p-best.Another best value that is tracked by the PSO is the best value obtained so far by any particle in the neighborhood of that particle. This value is called g-best.

C. Hybrid PSOGA: The drawback of PSO is that the swarm may converge prematurely. The underlying principle behind this problem is that, for the global best PSO, particles converge to a single point, which is on the line between the global best and the personal best

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positions. This point is not guaranteed for a local optimum. Another reason for this problem is the fast rate of information flow between particles, resulting in the creation of similar particles with a loss in diversity that increases the possibility of being trapped in local optima.The basis behind this is that such a hybrid approach is expected to have merits of PSO with those of GA. One advantage of PSO over GA is its algorithmic simplicity. Another clear difference between PSO and GA is the ability to control convergence. Crossover and mutation rates can subtly affect the convergence of GA, but these cannot be analogous to the level of control achieved through manipulating of the inertia weight. In fact, the decrease of inertia weight dramatically increases the swarm's convergence. The main problem with PSO is that it prematurely converges to stable point, which is not necessarily maximum. To prevent the occurrence, position update of the global best particles is changed. The position update is done through some hybrid mechanism of GA. The idea behind GA is due to its genetic operator's crossover and mutation. By applying crossover operation, information can be swapped between two particles to have the ability to fly to the new search area. The purpose of applying mutation to PSO is to increase the diversity of the population and the ability to have the PSO to avoid the local maxima

PSO-GA Approach : In this model the initial population of PSO is assigned by solution of GA. The total numbers of iterations are equally shared by GA and PSO. First half of the iterations are run by GA and the solutions are given as initial population of PSO. Remaining iterations are run by PSO.

D.Firefly Algorithm(FA): It is,based on the characteristics of fireflies.Every fireflies are unisex so each firefly will be attracted by other fireflies without caring about their gender.The attractiveness of a firefly depends on its brightness.The brighter will attract the less brighter.The attractiveness will decrease when the distance between two fireflies increase. The brightness of a firefly can simply be determined through objective function.Withβ0 is the attractiveness at r = 0, the decrease of attractivenessdepended on the distance also is defined like in the equation below

$$\beta = \beta_0 e^{-\gamma r_{ij}^2}$$

The movement of a firefly _ is attracted to another moreattractive (brighter) firefly $ is determined by:

$$x_i^{t+1} = x_i^t + \beta_0 e^{-\gamma r_{ij}^2}\left(x_j^t - x_i^t\right) + \alpha_t \in_i^t$$

In this equation, the second term is due to the attraction. The third term is randomization with αt being randomization parameter, and ∈ itis a vector of random numbers drawn from a Gaussian distribution or uniformdistribution at the time 0. If βo = 0, it becomes a simplerandom walk. On the other hand, if γ = 0, it reduces to avariant of Particle Swarm Optimization.

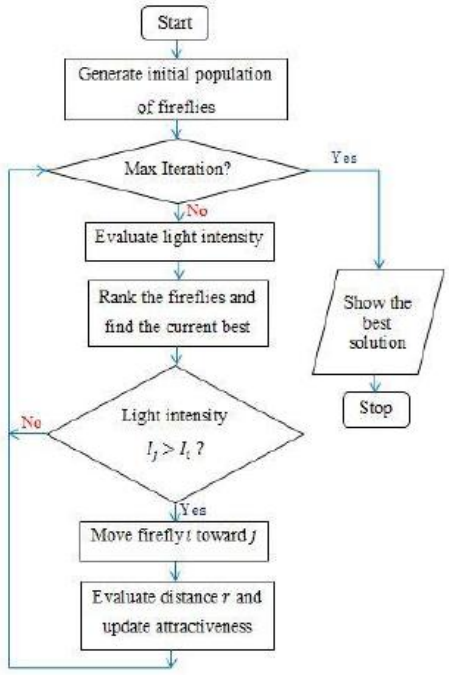

Figure 1: Flow chart of FA

Algorithm

In pseudocode the algorithm can be stated as:

Begin

1) Objective function: $f(\mathbf{x}), \quad \mathbf{x} = (x_1, x_2, \ldots, x_d)$;

2) Generate an initial population of fireflies $\mathbf{x}_i \quad (i = 1, 2, \ldots, n)$;.

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3) Formulate light intensity *I* so that it is associated with (for example, for maximization problems, or simply ;)
4) Define absorption coefficient γ

While (t <MaxGeneration)
fori = 1 : n (all n fireflies)
for j = 1 : n (n fireflies)

if ( ),

Vary attractiveness with distance r via ;
move firefly i towards j;
Evaluate new solutions and update light intensity;
end if
end for j
end fori
Rank fireflies and find the current best;
end while

Simulation Results Estimation of the sensor node position for a sparse network based on the FA approach isinvestigated. The simulation results are presented in thesection. We compared the proposed FA with the original GA PSO in terms of the solution quality and theprocessing time for the object function evaluations. . The goal of the optimization is tominimize this object function.

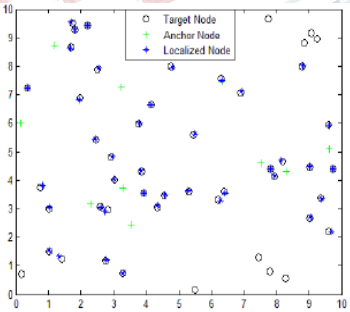

Figure 2: Location estimated by GAPSO

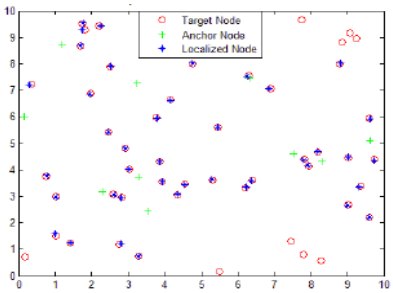

Figure 3: Location estimated by FA

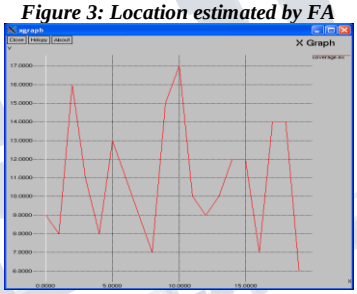

Figure 4 NS-2 scenario

Algorithm	No of iterations	Localization error
GA	13962	0.78
PSO	7697	0.64
PSOGA	5879	0.49
FFA	5336	0.28

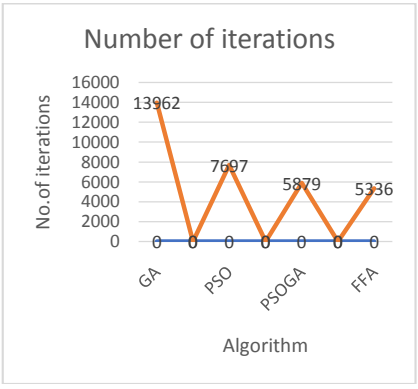

Figure 5. Number of iterations

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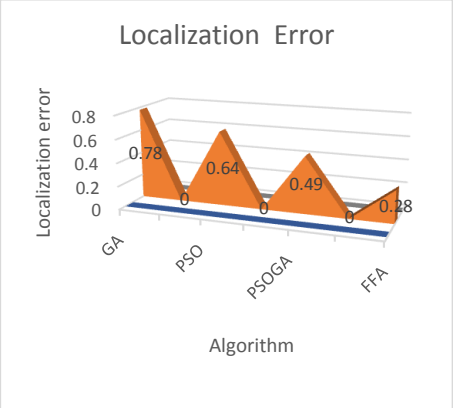

Figure 6 Localization error

III. CONCLUSION

This paper, proposed optimization algorithm, namely Firefly Algorithm (FFA) for the node localization in Wireless sensor networks (WSN). The implementation of optimization algorithms is important for sharing the computation load over several processors and achieving the individuals cooperating of optimization algorithms. In The new proposed algorithmis superior to both GA and PSO in terms of iterations,accuracy and time. The proposed communication strategycan be modified to solve multiobjective optimization problems. In addition,the application of firefly algorithm in combination of with other algorithms may form an exiting area for further research.

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