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HYBRID APPROACH FOR SENSOR DEPLOYMENT IN WSN

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ABSTRACT

Wireless Sensor Networks (WSNs) consists of arbitrarily placed tiny sensors which monitor the target field. Every location of the target field is said to be with at least one sensor. The sensors must be deployed in such a way that every sensor is efficiently used to monitor the target field with less coverage loss. Glow worm Swarm Optimization (GSO) technique is swarm intelligence based technique, which depends on the behaviour of glow worms (also called as lightning bugs or fireflies). In sensor node deployment optimization, GSO performs very well in terms of coverage and is used to achieve greater coverage with less sensor nodes in the network. The solutions obtained by hybrid approach which is based on GSO and Bioluminescent Swarm Optimization (BiSO) are better than the best solutions obtained by an efficient Glow worm Swarm optimizer alone. This approach is a free from differential equations and is a very efficient evolutionary algorithm. Non-Stochastic adaptive step-size movement strategy is implemented which is derived from GSO and BiSO. On the basis of considering dynamic deployment in WSNs, simulation results show that the hybrid approach yields greater coverage than the existing GSO technique.

Keywords: wireless sensor network, dynamic deployment, coverage, glow worm swarm optimization, bioluminescent swarm optimization.

1. INTRODUCTION

Wireless Sensor Networks (WSNs) have been effectively used in various strategic purposes. They have been used in the areas like surveillance, target tracking and classification [1]. WSN is a wireless sensor network consisting of many autonomous sensors which are spatially distributed or scattered either inside the field or very near to the target field to observe temperatures, vibration, sound, motion, humidity etc scenarios. Location of sensor nodes in the given field do not require pre-determination and these nodes should have self-arranging abilities [2]. These attributes provide WSNs a large variety of applications, such as health, military and commercial. In health, sensor nodes can be applied to patient monitoring. In the military, rapid deployment and self-organizing characteristics make WSNs available for communications, surveillance and reconnaissance applications. In commercial applications, the use of WSNs can be related to inventory management, product quality control and disaster area monitoring [3]. The discussion on applications of localization and positioning are made in [4] [5]. WSN's are very different from regular computer communication networks. WSN is a collaborative network where there exists many senders and one destination which is different from normal network that provides unicasting /multicasting/broadcasting. Protocols in WSN are different and so WSN is a unique variety of networks.

Sensor node consists of sensors, radio-transceiver, microcontroller and power source. Each sensor contains a computational unit or a programmable module which helps in performing computations, storage and bidirectional communication with other sensors in the network. Nodes can be placed in deterministic or in random fashion. Deploying the sensors in deterministic strategy is uncertain. Hence, nodes are deployed initially in random fashion. With these distinct scenarios, nodes are mobile which can re-arrange in the area and can broadcast the information with the other nodes of the system. Coverage is a crucial challenge in WSN and is associated with saving energy, network reconfiguration and connectivity. In general, it deals with sensor nodes placement in target field to achieve sufficient coverage in the target field such that every location of the target field is covered by minimum of one sensor. Maximum coverage is necessary for the efficient WSN [6] [10]. Coverage of sensor networks describes how well an area is monitored.

Connectivity in the network is said to maintained with communication range, r_c and sensing range, r_s where r_c is at least twice that of r_s (i.e., $r_c \geq 2*r_s$) [7]. Homogenous sensor nodes have a fixed sensing region and a fixed communication range. The goal is to achieve maximum sensing coverage with fewer number of sensor nodes.

This paper is arranged as: In section II, we review the literature work. Then, section III contains an abstract view of hybrid approach and its implementation. In section IV, we discuss parameter settings and section V describes the discussion of a wide range of experimental results followed by the conclusion.

2. RELATED WORKS

As the randomly deployed sensors in the target field is more than the sensors required, an energy-efficient method to deploy sensor nodes and to achieve greater coverage is to be considered. This method should have greater coverage rate with minimum moving distance and less time complexity. The art gallery problem aims to utilize less number of sensors in a polygon so that every location of the polygon is observed with minimum of one sensor [8]. This is an approximation algorithm based on geometry calculations for solving the problem. Many researchers proposed algorithms based on biological inspirations [11] [12] [13]. In the year 1995, Eberhart and Kennedy developed Particle Swarm Optimization (PSO) using the swarm behaviour such as bird and fish schooling

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in nature and this is called as swarm intelligence [14]. It is discussed in [15] that, Glow worm Swarm Optimization technique, after initial sensor deployment increases the coverage. Bioluminescent swarm optimization employs attraction based on luciferin instead of fitness-based among the sensors, as given in GSO. This algorithm uses the parameters γ and ρ, where γ is the luciferin enhancement constant and ρ is the luciferin decay constant. This also employs non-stochastic step size, in place of constant step size as in the GSO. This step size gets varied for every particle, based on its luciferin and is controlled by the parameters c_g and c_s [16].

The research of BiSO on sensor deployment recommended parameter values based on reasonable inference but not on precise theoretical analysis. Along with attraction towards the other agents that have higher luciferin value as in GSO, it also uses mass extinction and local search procedure. As the convergence to be made to the global optimum, proper parameter values selection is very essential and improper selection can lead to poor reliability. To explore for better assignment of parameter values, the effects of parameters on BiSO implementation were investigated in this work.

3. HYBRID APPROACH FOR SENSOR DEPLOYMENT

This paper aims to use hybrid approach inspired by Bioluminescent Swarm Optimization algorithm and Glow worm Swarm Optimization algorithm. It also provides the comparison study of GSO and hybrid approach. Glow worms emit light with a luminescent material which is luciferin. The light intensity released by these agents is directly proportional to the luciferin intensity related to it. These glow worms utilize the luciferin to connect to other glowworms in the neighbouring sensing range to communicate the profile information of their present position. The next position of glowworm is determined with the luciferin intensity of its neighbours. Every glowworm is attracted to its neighbouring glowworms having high intensity and chooses to move towards the neighbour that has luciferin more than this glowworm. These luciferin intensity movements partition the swarm of glowworms to disjoint subgroups [17].

A. General description of BiSO

The movement of sensors in BiSO is based on luciferin instead of fitness based among the particles, as proposed by the GSO. This BiSO technique is controlled by the parameters, luciferin decay constant and luciferin enhancement constant, i.e., ρ and γ, respectively. It also uses a non-stochastic step size according to luciferin value and which is controlled by c_s and c_g parameters that is different for every particle. The mass extinction mechanism is used in this algorithm which is explained in section C.

The drawback of GSO algorithm is the computational complexity and is overhead because of frequent distance calculations. BiSO does not calculate distance and considers an infinite radius for the neighbourhood.

B. Step size and convergence

In BiSO algorithm, it uses equation (1) to calculate the next location of the present particle:

$$y_i(t+1) = y_i(t) + s_0 * \left[\frac{y_j(t) - y_i(t)}{\|y_j(t) - y_i(t)\|}\right] + c_g * s_0 * \left[\frac{g(t) - y_i(t)}{\|g(t) - y(t)\|}\right] \quad (1)$$

Where $y_i(t)$ is the present particle location, s_0 is the current step size of the agent and g is the global best position. As in GSO, BiSO does not use fixed step size, but uses variable step.

$$s_0 = s * \frac{1}{1 + c_s * l_i(t)} \quad (2)$$

Where s is the maximum step, $l_i(t)$ is the luciferin of the sensor, and c_s is a slowing constant. This helps the nodes with overlaps move faster for better regions.

C. The local search procedure

The Local Unimodal Sampling (LUS) is a simple and quick technique for numerical optimization that is satisfactory to unimodal search spaces [9]. As weak local search procedure is very important for the BiSO algorithm as this reduces the computational effort on worse particles. Random sampling is done within the radius starting from the base position and the radius is decreased exponentially [16].

D. Mass extinction

Mass Extinction takes corrective measures to avoid early stagnation. This method will repeat till either target solution is found or maximum iteration is reached. This procedure is used often in many evolutionary algorithms [19] [20] [21] although not used in GSO.

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Algorithm

1. Start
2. Initialize dimensions - rangeX and rangeY, r_c, r_s, Max_Iter
3. Set N=Number of sensor nodesand set each node with luciferin_value= light0
4. Let $y_i(t)$ be the location of node i at time t
5. Deploy sensors randomly
6. Calculate
   maxC=min(1,Max_Covered_area/Total_area), where Max_Covered_area=N*pi*rs^2
7. Calculate Coverage for each iteration which is C(Iter)
8. fitness=C(Iter)-maxC
9. While (fitness > 0.1 && iteration<Max_Iter) repeat steps10 to 14
10. For each glowworm update luciferin from past luciferin and current position, derive current luciferin as done for GSO
    $$y_i(t+1) = y_i(t) + s_0 * \left[\frac{y_j(t) - y_i(t)}{\|y_j(t) - y_i(t)\|}\right] + c_g * s_0 * \left[\frac{g(t) - y_i(t)}{\|g(t) - y(t)\|}\right]$$
11. Update particle step_size
    $$s_0 = s * \frac{1}{1 + c_s * l_i(t)}$$
12. Find new positions with neighbourhood update based on non-stochastic step size
13. Perform Local_Search
14. Perform Mass_Extinction
15. End

Algorithm 1: Pseudocode of hybrid approach for sensor deployment

4. EXPERIMENTAL ENVIRONMENT

An optimal algorithm would contain less parameter values and the algorithm parameters are set to constant values yielding best performance over a wide variety of problems.

In the experiments conducted, the size of the network field is fixed of 100X100.As the communication range is double that of the sensing range, they are taken as 10m and 5m respectively. The number of sensors is considered from a range of 50 to 200. In ideal case, 200 sensors are maximum to provide full coverage in a 100 X 100 region; and this is derived from the formula of number of circles (N) required to cover a field [18].

$$N = \frac{2 * A}{3\sqrt{3} * {r_s}^2} \quad (3)$$

Where N is the number of sensors, A is the target area and r_s is the sensing radius of the sensor node in the target field.

Termination of the algorithm is very important factor in swarm intelligence algorithms. There are numerous methods for terminating algorithm such as determining a constant number of iterations or until a predefined value for fitness acquired or in Maximum iterations the fitness value doesn't change. Here we use fitness equal to 0.1and maximum number of iterations equal to 200.

Table-1. Parameter values used in simulation study.

Parameter	Function	Value
r_s	Sensing Range	5m
r_c	Communication Range	10m
N	Number of Sensors	200
Area	Total Area	100X100
c_{th}	Threshold Value	0.01
$light_0$	Initial Luciferin	10
c_s	Attraction to Global Best	0.03
c_g	Slowing Constant	5
ρ	Luciferin Gain Constant	0.4
γ	Luciferin Decay Constant	0.6
s_0	Step Size limit	1.0
e^T	Number of Stagnated Iterations to Enable Explosion	10

5. RESULTS OF HYBRID APPROACH

The Simulation illustrations were made using MATLAB on both GSO and hybrid approach for an area of 100*100 and varied values of sensor nodes. The hybrid approach is conducted for variable values on N, but it is observed that the coverage is more with N=200 for an area of 100 X 100. It is assumed that all the nodes have same sensing and communications ranges. The initial population is created by random deployment and the objective fitness function for this population is determined. The maximum numbers of iterations were taken as 200. Figure-1shown below depicts the random deployment of sensors. Figures

2 and 3 depict the arrangement of sensors after GSO and hybrid algorithm implementation.

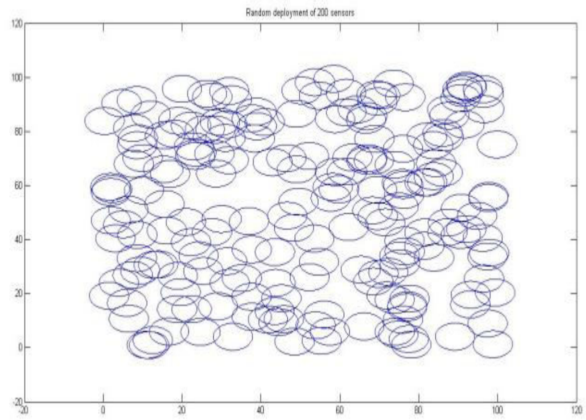

Figure-1. Random deployment of sensors with N=200.

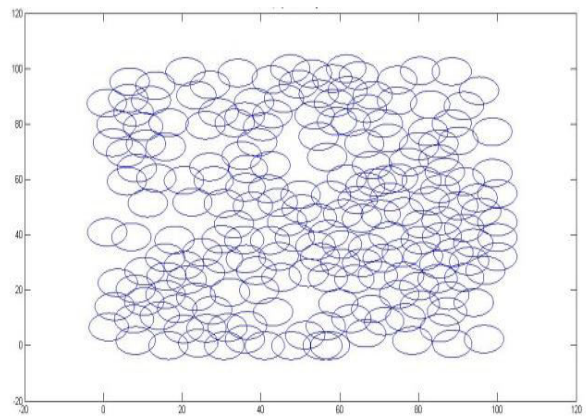

Figure-2. Deployment of 200 sensors using GSO.

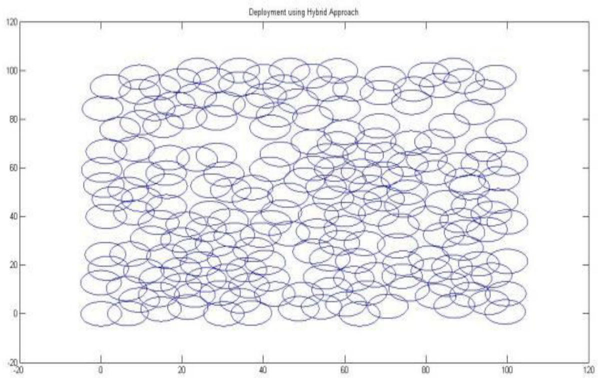

Figure-3. Deployment of 200 sensors using hybrid approach.

Figure-4 and Figure-5 depicts the coverage versus the number of iterations using 200 and 250 sensors respectively. Even though the coverage calculated by this hybrid algorithm does not match the ideal case instead; it follows the incremental approach with GSO. It is observed that hybrid approach provides faster convergence and better performance in coverage rate when compared with GSO.

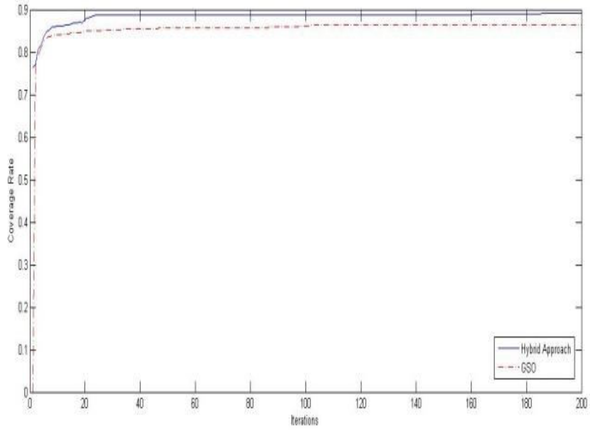

Figure-4. Coverage rate versus iterations with N=200.

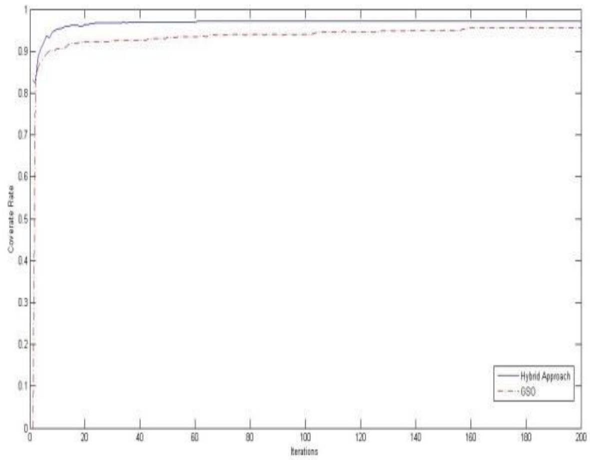

Figure-5. Coverage rate versus iterations with N=250.

As the experiments are conducted with nodes range from 50-250, Table-2 shows the statistical results of coverage area with sensor nodes N=50,100,150,200 and 250. The results show that the prosposed hybrid approach covers more area than GSO algorithm. Figures 6 and 7 show that the total moving distance using hybrid approach is far less than that of the GSO and hybrid algorithm converges quickly.

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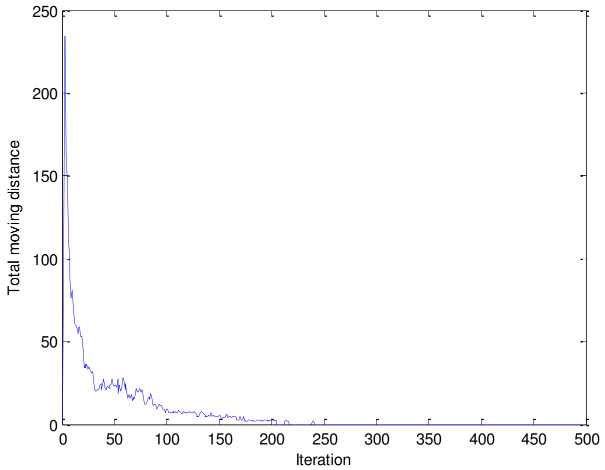


Figure-6. Total moving distance using GSO.

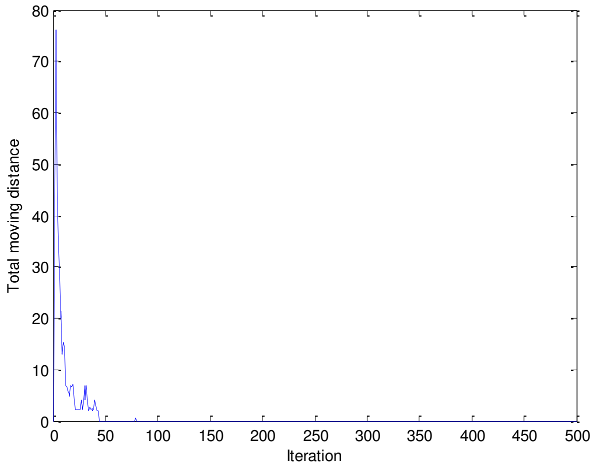
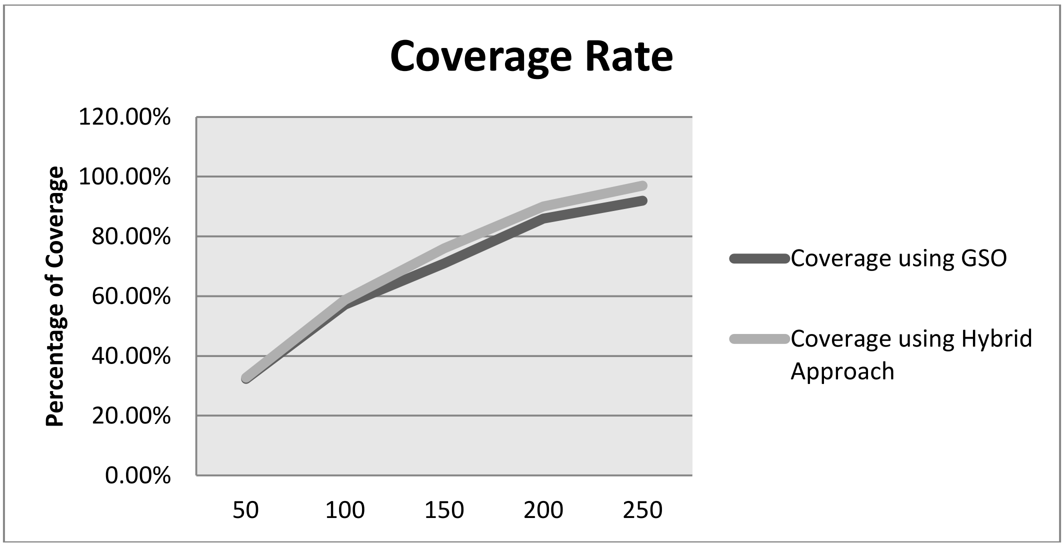


Figure-7. Total moving distance using hybrid approach.

Table-2. Coverage rate of GSO and hybrid approach.

Number of sensors	Coverage using GSO	Coverage using hybrid approach
50	32.3%	32.7%
100	57.2%	58.8%
150	71%	76%
200	86%	90%
250	92%	97%



6. CONCLUSIONS

Several interpretations of coverage using hybrid approach on wireless sensor networks were presented. Implementation of hybrid approach provides better coverage and the optimal arrangement of nodes by conserving less energy. Finally, this hybrid algorithm is for deploying sensors in WSN. The results show that the algorithm has faster Convergence speed and less traverse distance. The research of BiSO is just at the beginning, there are still many problems for studying thoroughly. In addition, BiSO algorithm with a combination of other algorithms may produce exciting results and help in further research.

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