Heuristic Approach for Optimizing the localization of wireless sensor Networks

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Abstract

Wireless Sensor Networks (WSNs) are networks of spatially distributed autonomous nodes used to perform various monitoring tasks. Localization is a challenging issue in WSNs. Many approaches have been proposed to determine the positions of randomly deployed sensor nodes. In this paper, an attempt is made for optimizing the localization of the sensor nodes. A hybrid approach is proposed to improve the efficiency and accuracy and overcome the drawbacks like getting trapped at a local extreme in the optimization process. In the proposed heuristic algorithm the idea of Particle swarm optimization is merged into the chemotaxis of bacterial foraging optimization algorithm to speed up the convergence rate and the elimination probability is selected according to the energy of bacteria to improve the global searching ability. Also the crossover technique of genetic algorithm is introduced in the reproduction stage to improve the evaluation of optimal objective function values.

Keywords: WSN, Bacterial foraging algorithm (BFA), Particle Swarm Optimization (PSO), Hybrid Algorithm (BFA-PSO-GA), genetic algorithm (GA).

Introduction

Wireless Sensor Networks (WSN) consist of tiny wireless battery operated devices capable of sensing, computing and communicating. WSNs help to disseminate information from various environments which would serve many applications. The strength of wireless sensor network is the ability to deploy large number of nodes with less human intervention and so it’s sometimes referred as self-configurable network.

In sensor networks, nodes are deployed in a random manner where there is no prior knowledge of the location. Determining the spatial-coordinates of the randomly deployed node is referred to as localization which is an area of active research.

A WSN can comprise of M nodes, with a communication range of $T_a$ distributed in a 2-D field. The WSN is represented by the Euclidean graph $G = (V, E)$, where $V = \{v_1, v_2, ..., v_m\}$ is the set of sensor nodes. $\{p, q\} \in E$ if the distance between $v_p$ and $v_q$ is $d_{pq} \leq T_a$. The set $U$ represents the unknown or non-anchor nodes whose location has to be estimated. The set $A$ of nodes represents the anchor nodes which has prior knowledge about its location. The localization problem is to transform the non-anchor nodes into settled or anchor nodes, by finding the position $(x_u, y_u)$ of as many $u \in U$ as possible from the set of anchor nodes $A$ and their positions $(x_a, y_a)$, for all $a \in A$.

Localization is categorized into range based which needs the node to node angle or distance information [2] which are derived from time of arrival (TOA), angle of arrival (AOA), and received signal strength indicator (RSSI) etc and range-free which doesn’t require any such information [3].

Localization deals with estimating the distance between the settled anchor nodes and the unknown non-anchor nodes using the received signal strength, then compute the position of unknown nodes using the estimated distance. Then refine the determined node positions iteratively using range information and positions of neighboring nodes. This can be done by solving the set of simultaneous equations or by using an optimization algorithm which increases the accuracy of localization. An overview of the various components of the localization systems for WSNs is presented in [2]. The performance of the localization depends directly on these components.

The rest of this paper is organized as follows. Brief related works of BFA, PSO and GA are presented in Section II. Hybrid approach for the optimization of localization is discussed in Section III. Details of the NS2-based simulations are presented and the results are discussed in Section IV. Finally, the concluding remarks are given in Section V.

Related Work

In PSO algorithm the objective function need not be differentiable so that it is more appropriate for irregular and dynamic optimization problems. PSO algorithm is used to train the hidden markov model (HMM), the machine learning technique in speech recognition in [6]. In PSO the particles change their position based on the knowledge of themselves and the other particles so it attempts to find the global optimum solution. PSO has also been applied for a minimization problem, Ackley problem to overcome the possibility of getting trapped at local optimum solution by eliminating the particles having lesser fitness values after several iterations thereby increasing the speed.
Saber et al proposed an evolutionary algorithm bacterial foraging technique with PSO based evolution in [4] to solve the economic load dispatch (ELD) problem. The proposed approach attempts to minimize the generation cost with respect to the constraints like generation limits, system power balance, ramp rate, network losses etc. The movement principle in PSO is adopted to replace random walk of BFA. The hybridized algorithm helps to find an optimum solution even in a complex high dimensional space.

A modified BFA called cooperative bacterial foraging optimization (CBFO) algorithm is proposed in [7] having two stages by altering the run length parameter. Larger run length helps to locate the global optimum region and smaller step size attempts to find the optimum point. They have validated the algorithm in finding the optimum value of several benchmark functions.

A hybrid approach PSO and BFA has been proposed in [8], where PSO is used to exchange the social information and BFA helps to find the new solution faster using elimination and dispersal approach. The random walk of the bacteria in BFA is reduced by considering the knowledge of position and velocity of the swarm and has been applied to tune PID controllers for various testing systems. A hybrid BFA-PSO approach has also been applied to find the global optimum of benchmark functions [10].

A hybrid algorithm combining GA, PSO and BFA has been addressed in [9] where selection, crossover, and mutation operators of GA are used to increase diversity of the search and movement concept of PSO is utilized to replace random walk concept of BFA. Finally, in the elimination and dispersal events, the eliminated bacteria are not dispersed to new random position but generated via mutation. The algorithm has been used to tune PD-like fuzzy pre-compensated control for two-link rigid-flexible manipulator.

**Proposed Work**

In an optimization problem, the task is to find global optimum in the search space. There are several challenging properties such as there may be many local optima; the size of the search space may be so large that may impact on computation time of the search process. Various numerical analysis based tools have been developed but require more computational efforts. In general, biologically-inspired algorithms developed by mimicking biological processes such as evolution and natural selection, social systems and foraging with the main aim is to seek potential and possible alternative techniques for solving highly complex problems that may not be achieved by using existing computational methods such as linear programming and gradient descent based methods.

A new heuristic approach hybridizing the BFA-PSO-GA algorithm is introduced to determine the global optimized position of the randomly deployed nodes in the search space that maximizes the fitness function $f(\lambda) = \log P(o/\lambda)$ [6]. The fitness function is used to determine which solution is better than the others and is instrumental in determining the direction as well as magnitude of the velocity vector iteration.

Bacterial Foraging Optimization technique is evolved from the E. Coli bacteria’s mechanism of finding the places with higher nutrient value and avoiding noxious places. BFA is a population-based numerical optimization algorithm. It has been applied for solving practical engineering problems like optimal control, harmonic estimation, channel equalization etc [4].

![Flowchart for Hybrid BFA-PSO](image.png)

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Chemotaxis is a foraging behavior that captures the process of optimization, where the non anchor (target) nodes try to climb up to the transmission range. From its current position, target node will move to the position that has a minimum fitness value. The “speed” of the node movement is controlled by the chemotactic step size $C$. Change in the direction of movement is tumbling whereas moving in the same direction is swimming. The direction of movement after tumble is based on the position of every node and its velocity. At each iteration $i$, velocity $v$ and position $x$ of each node are updated using (1) and (2)

$$V_i = V_{i-1} + c1 \times \text{rand}(\cdot) \times (pbest - X_i) + c2 \times \text{rand}(\cdot) \times (gbest - X_i)$$

(1)

$$X_i = X_{i-1} + V_i$$

(2)

$V_i$ is the node’s velocity. Initially the values of the velocity are randomly generated within the range $[-V_{m}, V_{m}]$ where $V_{m}$ is the maximum value that can be assigned to any $V_i$. $X_i$ is the nodes current position. pbest and gbest are the particle and swarm best values. $\text{rand}(\cdot)$ is a random number between 0 and 1. $c1$, $c2$ are learning factors governing the cognition and social components. Usually $c1 = c2 = 2$.

Thus, the movement of target node from one position to another position will be the sum of current position and the step size and direction generated from PSO. By this the nodes will move towards the global optimum position every time. If at target node position, the fitness value is lower than the previous value then the target node will move one step in the same direction with the step size and is continued until a minimum fitness value is reached but only for a certain number of steps, $N_r$. After swims, the nodes have to tumble. Target nodes will reproduce very fast if the RSSI is high and will die if less so that the population size will decrease significantly. This mechanism keeps the node’s population constant.

To model the reproduction mechanism, after $N_{ch}$ chemotactic step size, the fitness values of all the target nodes are sorted in ascending order based on their accumulated cost function value.

Using the crossover mechanism of genetic algorithm, the nodes having highest $j_{fit}$ is eliminated and the other nodes are considered as the parent node for the next generation. Select two sets of parent node from the fittest group and cross over them with probability to create number of off springs (new nodes).

After reproduction steps, the target nodes which have probability value (between 0 and 1) lower than a certain threshold value ($p_{ed}$) are eliminated and dispersed to another location and nodes which have probability value higher than $p_{ed}$ keep their current position.

After elimination and dispersal event, node will start chemotaxis until maximum reproduction steps are achieved and then followed by other elimination and dispersal events. This routine is done until maximum $N_r$ elimination and dispersal events are achieved. A detailed pseudo code for hybrid BFA-PSO-GA is given in Algorithm 1.

Algorithm 1 Hybrid BFA-PSO-GA
1. Initialize $N_{ch}$, $N_r$, $N$, $Ns$, $C$, $V$, $X$
2. Elimination-Dispersal loop: while $l <= N_e$
   3. $l = l + 1$
   4. Reproduction loop: while $m <= N_r$ do
   5. $m = m + 1$
   6. Chemotaxis loop: If $n <= N_ch$
   7. For each node $i$
   8. While ($sm < N_{ch}$) do
   9. $sm = sm + 1$
   10. $pbest = Xi + c2 \times \text{rand}(\cdot) \times (gbest - Xi)$
   11. Compute $Xi = Xi_{old} + Vi$
   12. If ($f(Xi) > f(Xi_{old})$) do
   13. Let $f(Xi) = f(Xi_{old})$
   14. Compute new $Xi$
   15. Else
   16. $sm = N_{ch}$
   17. End if
   18. End while
   19. Compute $j_{fit}$
   20. Eliminate node having the highest $j_{fit}$ and the other nodes are considered as the parent node for next generation.
   21. Select two sets of parent node from the fittest group and cross over them with probability to create number of off springs (new nodes)
   22. Append the parent node ($j_{fit}$) and the newly created nodes to form the complete set of nodes.
   23. End for
   24. End if
   25. End while
   26. Eliminate the node having $ped$ and create new node at a random position
   27. End while

The node localization in a WSN is optimized in the following way.

1. $N$ target nodes and $M$ anchors are deployed randomly in a sensor field. Anchor nodes are aware of their location and they transmit their location information frequently. The nodes that get localized in first iteration serve as references in the next iteration.
2. Nodes that come within transmission range of three or more anchor nodes are said to be localizable.
3. Each localizable node estimates its distance from its neighboring anchor node as $d_m = d_m + n_m$, where $d_m$ is the actual distance given by $d_m = \sqrt{(x-x_m)^2 + (y-y_m)^2}$

Here, $(x, y)$ is the position of the target node, and $(x_m, y_m)$ is the coordinates of the $m^{th}$ anchor node. The noise $n_i$ has a random value uniformly distributed within the range $d_m \pm d_{m_{ed}} (\frac{p_n}{100})$.

4. Each localizable node runs the hybrid BFA-PSO-GA optimization algorithm and searches for the best position that minimizes the localization error.
5. The total Estimation error is computed as follows:

$$E_L = \frac{1}{N_t} \sum_{m=1}^{L} (x-x_m)^2 + (y-y_m)^2$$

(3)

The above steps are repeated for all localizable target nodes.
Simulation and Results
Simulation of the WSN and its performance evaluation have been implemented in NS2. The sensor nodes are deployed randomly in a sensor field having dimensions of 1000 × 1000sqm. The transmission range of the anchor node is 150m. 10% of the total number of nodes is taken as anchor nodes. The General Network Topology Parameters are:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Channel Type</td>
<td>Wireless Channel</td>
</tr>
<tr>
<td>Radio-Propagation Model</td>
<td>TwoRayGround</td>
</tr>
<tr>
<td>Packet Size</td>
<td>512 bits</td>
</tr>
<tr>
<td>Routing Protocol</td>
<td>AODV</td>
</tr>
<tr>
<td>Total no. of nodes</td>
<td>100</td>
</tr>
<tr>
<td>Total Simulation Time</td>
<td>200</td>
</tr>
<tr>
<td>Model</td>
<td>Energy Model</td>
</tr>
</tbody>
</table>

The parameters are set for the hybrid algorithm as follows:
1) number of chemotactic steps \(N_c = 5\)
2) number of swims \(N_s = 20\)
3) number of reproduction steps \(N_r = 5\)
4) number of elimination-dispersion steps \(N_{ed} = 5\)
5) probability of elimination-dispersion event \(p_{ed} = 0.1\)
6) acceleration constants \(c_1 = c_2 = 2.0\)
7) inertia weight \(w = 0.5\)
8) node’s velocities: \(v_m = 10\)
9) number of iterations = 10

The following Performance Metrics are analyzed:
- Percentage of nodes localized
- Localization Error
- Average Energy Consumption

Table I shows the effect of noise \(p_n\) in the distance measurement on the accuracy of localization. The average localization error and number of non localized nodes \(N_{NL}\) is less for the proposed algorithm than BFA.

Table II summarizes the number of nodes localized at each iteration and the localization error. Since the localization method that we are using is iterative, the number of nodes localized \(N_L\) increases with iterations which in turn increase the number of references available for the remaining nodes. In addition, the hybrid algorithm requires only fewer numbers of iterations than that of BFA.

Table I. summary of results of bfa-psos-ga and bfa based optimization

<table>
<thead>
<tr>
<th>pn=5</th>
<th>pn=2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (N_{NL})</td>
<td>Mean (E_L)</td>
</tr>
<tr>
<td>Mean (N_{NL})</td>
<td>Mean (E_L)</td>
</tr>
<tr>
<td>BFA-PSO-GA</td>
<td>0.006</td>
</tr>
<tr>
<td>BFA</td>
<td>0.133</td>
</tr>
</tbody>
</table>

Table II: summary of results of hybrid algorithm and bfa based optimization with n=100, m=10 and transmission range 150m

<table>
<thead>
<tr>
<th>Iterations</th>
<th>(N_L)</th>
<th>(E_L)</th>
<th>(N_{NL})</th>
<th>(E_{NL})</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>89</td>
<td>0.0182</td>
<td>74</td>
<td>0.1961</td>
</tr>
<tr>
<td>2</td>
<td>97</td>
<td>0.0171</td>
<td>87</td>
<td>0.1150</td>
</tr>
<tr>
<td>3</td>
<td>100</td>
<td>0.0076</td>
<td>92</td>
<td>0.0711</td>
</tr>
<tr>
<td>4</td>
<td>100</td>
<td>0.0076</td>
<td>97</td>
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</tr>
<tr>
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<td>7</td>
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<td>100</td>
<td>0.0306</td>
</tr>
<tr>
<td>8</td>
<td>100</td>
<td>0.0076</td>
<td>100</td>
<td>0.0306</td>
</tr>
</tbody>
</table>

Figure 2: Localization Error with respect to the number of nodes

Variation of localization error with respect to the number of nodes is shown in Fig 2.

Figure 3: Dependence of number of nodes localized on the speed

Localization Accuracy increases when the number of nodes increases. Figure 3 shows that the number of nodes localized increases when the speed is increased. The localization error increases with increase in the percentage of noise is shown in Figure 4. It is clear that the percentage noise is an important parameter that influences the localization accuracy.
Figure 4: Localization Error with respect to the Error factor

Figure 5: Average Energy Consumption Vs No. of nodes

The energy consumption graph shows that the hybrid approach consumes less energy when compared with the BFA.

Conclusion
The proposed Heuristic Bio-inspired algorithm is based on the modification of BFA. The convergence speed and accuracy is improved by finding the new position based on the previous best position pbest and gbest. The convergence speed is the number of steps needed to converge to the optimum value. The crossover mechanism of genetic algorithm introduced in the reproduction stage helps to find the global optimized position of the nodes. From the simulation results, the proposed algorithm increases the speed and accuracy in such a way by reducing the total energy consumption.

References


