Optimized Distributed Range-Based Node Localization in Wireless Sensor Networks

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Abstract: This paper proposes range-based distributed single-hop and scalable 3D node localization algorithm by using the application of Biogeography Based Optimization in anisotropic Wireless Sensor Networks (WSNs). In anisotropic networks, radiation patterns are not uniform. An anisotropic property of propagation media and heterogeneous properties (different battery backup statuses) of the devices are considered.

Keywords: Wireless Sensor Networks (WSNs), Biogeography Based Optimization (BBO), Anisotropic Environment

1. Introduction

Wireless Sensor Network (WSN) is an emerging technology, which has captured the attention and vision of many researchers, encompassing a broad spectrum of ideas since the last decade. Despite their variety, all WSNs have certain fundamental features in common. Perhaps, the most important is that they are incorporated in the real world. Hence, a WSN can be defined as a network for automatic detection of variables. Prevention of catastrophes and recovery of information from urban disaster are some of the many possible uses for this emerging technology. Such a close relationship with the physical world is a dramatic contrast to much of traditional computing, which often exists in a virtual world. Hence, a WSN can be considered as a retrieval of information anytime and anywhere by collecting, processing, analyzing and disseminating data; and can actively participate in the formation of a smart environment [1, 2, 3].

Node localization is an emerging technology and has a number of critical research issues in WSNs. It is worthwhile, if each node in the network is equipped with position finding instruments like GPS which, of course, enhance the cost of the network and consumption of energy is also increased. Localization techniques are applied to calculate the location of the sensor nodes whose coordinates are not known in a network (termed as target nodes) using available a priori knowledge of positions of typically a few specific sensor nodes called anchors, based on inter-sensor parameters/measurements such as connectivity distance, Time of Arrival (TOA), Time Difference of Arrival (TDOA), Angle of Arrival (AOA), etc. [4, 5].

2D localization assumptions are violated in underwater, atmospheric and space applications where height of the network can be substantial and nodes are distributed over a three-dimensional (3D) space. For example, underwater sensor networks (USNs), which are 3 dimensional, have attracted a lot of attention recently [6, 7]. In USNs, nodes may be placed at different depths of an ocean and thus the network becomes three-dimensional. Better weather forecasting and climate monitoring can be done by deploying three-dimensional networks in the atmosphere. This paper proposes the application of BBO algorithm for range-based 3D node localization in anisotropic WSNs. Algorithms performed better in terms of number of nodes localized; localization accuracy and computation

The rest of the paper is organized as follows: Literature Survey on WSN Localization is presented in Section II. Section III ushers the readership into a gentle overview of BBO algorithm used for localization in this work. This is followed with implementation of above said algorithms in section IV. Section V presents simulation results and comparative study. Finally, section VI presents conclusions and makes a projection on possible future research paths.

2. Literature Survey

A number of localization techniques have been proposed in the past and we still require a robust one. A detailed survey of the relevant literature is available in [8, 9, 10]. Soft computing plays a crucial role in optimization problems. WSN is treated as multi-modal and multidimensional optimization problem and addressed through population based stochastic techniques. A few GA-based node localization algorithms are presented in [11, 12, 13], that estimate optimal node locations of all one-hop neighbors. A two phase centralized localization scheme that uses Simulated Annealing Algorithm (SAA) and GA is presented in [14]. PSO-based algorithm is proposed in [15, 16] to minimize the localization error. In [17], two intelligent localization schemes for WSNs are introduced for range-free localization, which utilize received signal strength (RSS) from the anchor nodes. In the first scheme, the edge weight of each anchor node is separately calculated and combined to compute the location of sensor nodes. The edge
weights are modeled by a Fuzzy Logic System (FLS) and optimized by the GA. In the second scheme, the localization is approximated as a single problem where the entire sensors’ locations from the anchor node signals are mapped by a Neural Network (NN) [18]. A two-objective evolutionary algorithm which takes concurrently into account, during the evolutionary process, both the localization accuracy and certain topological constraints induced by connectivity considerations using metaheuristic approach, namely Simulated Annealing (SA), is proposed in [19]. In [20, 21], the perpendicular bisector strategy, the virtual repulsive strategy, and the velocity adjustment strategy are properly combined to enhance localization efficiency. The velocity adjustment strategy for the mobile anchor node automatically tunes its velocity. The perpendicular bisector strategy locally adjusts trajectory for the mobile anchor node, which ensures that unknown nodes obtain enough non-collinear anchor coordinates as soon as possible. The virtual repulsive strategy impels the mobile anchor node to rapidly leave the communication range of location-aware nodes or returns to the surveillance region after the mobile anchor node goes out of the boundary. An error model for the estimations of localization is proposed in [22], which gives a two-stage search procedure that combines minimization of an error norm function with maximization of a maximum likelihood function to solve the problem. An empirical study of the performance of several variants of the guiding functions, and several metaheuristic are used to solve real Localization Distance (LD) problem presented in [23]. Each target node is localized under imprecise measurement of distances from three or more neighboring anchors/settled nodes. The method proposed in this paper has following advantages, i.e., location accuracy, resilience to error and noise, coverage and cost.

3. Application of BBO for Node Localization in WSNs

Nature is a rich source of ideas for optimization. Quality of nature-inspired algorithms is assigned to their accuracy, and their meek computational burden. To achieve better and fast solution, application of BBO algorithm is applied for range-based distributive 3D node localization in this paper. BBO algorithm provides matured convergence and better accuracy as compared to the PSO method proposed in [24, 25]. An overview of BBO is given next subsection.

A. Biogeography Based Optimization

Biogeography is the study of migration, speciation, and extinction of species, that has often been considered as a process which enforces equilibrium in the number of species in habitats [26, 27, 28, 29]. A habitat is an ecological area that is inhabited by plant or animal species and which is geographically isolated from other habitats. Each habitat is classified by Habitat Suitability Index (HSI) that is termed as fitness in other EAs. The features that characterize habitat are called Suitability Index Variables (SIVs). Habitats with high HSI have large population, high emigration rate, µ, simply by the virtue of large number of species that migrate to other habitats. The immigration rate, λ, is low for these habitats as these are already saturated with species. Habitats with low HSI have high immigration, µ, and low emigration, λ, because of sparse population. The suitability index of habitats with low HSI is likely to improve with the influx of species from other habitats as it is a function of its biological diversity. However, if HSI does not increase and remains low, species in that habitat go extinct and this leads to additional immigration. For the sake of simplicity, t is safe to assume a linear relationship between a habitat HSI and its immigration and emigration rates and, further the rates are same for all habitats. The immigration and emigration rates depend upon the number of species in the habitats. These relationships are shown in Fig. 1. The values of immigration and emigration rates are respectively given as:

\[ \lambda = I \left(1 - \frac{k}{N}\right) \]  

and

\[ \mu = \frac{E}{N} \]  

![Fig. 1: Habitat Immigration and Emigration rate v/s Number of species](image)
Where \( I \) is the maximum possible immigration rate; \( E \) is the maximum possible emigration rate (\( I \) is not necessarily equal to \( E \)); \( k \) is the number of species of the \( K_{th} \) individual, \( n \) is the number of species. In Fig. 1, \( S_{max} \) is the maximum number of species in a habitat. The flow chart of the BBO algorithm is given in Fig. 2. For a pseudo-code of the algorithm, one may refer to [30].

## 4. BBO-Based 3D Localization

### A. Problem Statement

The main objective is to find out the 3D coordinates of \( N \) target nodes by using prior known locations of a total of \( M \) anchor nodes with single hop range-based distributed technique, deployed in anisotropic networks and the pair-wise distance information \( d_{ij} \) between \( i_{th} \) anchor and \( j_{th} \) target node of a network of total \( N_T = (N + M) \) nodes. To find 3D coordinate of the target nodes, a total of 3N unknown coordinates \( \theta = (\theta_x, \theta_y, \theta_z) \), where \( \theta_x = [x_1, x_2, ..., x_N] \), \( \theta_y = [y_1, y_2, ..., y_N] \), and \( \theta_z = [z_1, z_2, ..., z_N] \), are to be estimated using the known anchor nodes.
coordinates \((x_{N+1}, x_{N+2}, \ldots, x_{N+M})\), \((y_{N+1}, y_{N+2}, \ldots, y_{N+M})\) and \((z_{N+1}, z_{N+2}, \ldots, z_{N+M})\). In a 3D environment, each node that falls within transmission radii of four or more anchor nodes is referred as a localizable node.

In the absence of RSS information, each localizable target node \((x, y, z)\) calculates its Euclidian distance from each of its neighboring anchor nodes (where neighboring anchor nodes are considered to be the ones which are within the transmission radii of the considered target node), as given in (3):

\[
d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2}
\]

where \((x, y, z) = \text{target node coordinates}\) and \((x_i, y_i, z_i) = i_{th} \text{'neighboring' anchor node coordinates}\) \((i\) varies from 1 to \(M)\). The effect of anisotropic environment conditions is simulated. Therefore, the distance from each neighboring anchor node is given in (4):

\[
\bar{d}_i = (d_i + \eta_i)
\]

Where \(\eta_i\) is actual distance given by (3), \(\bar{d}_i\) is measured distance between target node and the \(i\)th anchor node with Gaussian noise \(\eta_i\). The mean square error between a target node and its neighboring anchor nodes is considered as the objective (problem) function for the proposed problem. Due to the inaccuracies of distance measurement techniques, the ranging errors are generated between target node and neighboring anchor nodes. Therefore, the objective function to be minimized using nature-inspired techniques is given by (5):

\[
f(x_n, y_n, z_n) = \frac{1}{M} \sum_{i=1}^{M} \left( \sqrt{(x_n - x_i)^2 + (y_n - y_i)^2 + (z_n - z_i)^2} - \bar{d}_i \right)^2
\]

Where \(M \geq 4\) = number of neighboring anchor nodes, \((x_n, y_n, z_n)\) are estimated target node coordinates. Towards presentation of overall statistics of the results, after getting the coordinates of all localizable nodes (total NL nodes), the mean localization error is computed from the distances between the actual node location and the measured/estimated node locations, for \(n = 1, 2,\ldots,N_L\) determined for both cases of HPSO and BBO, as in (6):

\[
E_L = \frac{1}{N_L} \sum_{n=1}^{N_L} \left( \sqrt{(x_n - \bar{x}_n)^2 + (y_n - \bar{y}_n)^2 + (z_n - \bar{z}_n)^2} \right)
\]

5. Simulation Results and Discussion

In this section, the effectiveness of the proposed application of BBO-based distributed node localization algorithms are assessed through panoptic simulations carried out in MATLAB environment. Forty target nodes and 10 anchor nodes are randomly deployed at sensor field of \(100l \times 100l\) units, where \(l\) denotes the unit placement length. Each anchor node has a maximum transmission range of \(R = 30l\) units. The distance between each pair of \(i_{th}\) anchor node and \(j_{th}\) target node is calculated to emulate the RSS information. This distance will be considered as true distance, \(d_{ij}\), if the distance between a pair is less than the radio range, \(R\), of the \(i_{th}\) anchor node. In the proposed methods, no specified ranging method is used. However, the centroid of the neighboring anchor nodes is considered as initial position of the each target node. The calculated distances between a target node and anchor nodes in its transmission range are assumed to blur due to anisotropic environment conditions. In the iterative process, the target nodes which could not be localized either due to not being within the specified area or due to less number of neighboring anchor nodes (i.e., minimum 4 for 3D) are considered as un-localizable nodes. For the next iteration, the localized nodes are considered as pseudo-anchor nodes, to localize the remaining target nodes. This decreases the probability of the ambiguity (wrong selection of anchor node). Other strategic settings are specific to BBO algorithm as discussed below:

1. Population size (i.e., number of species) = 20
2. Max. no. of iterations for each trial = 100
3. Probability of mutation = 0.05
4. Noise variance = 2, 6 and 8 (for three set of simulation experiments)
5. DOI = 0.01
6. Number of trials = 30

Thirty trials experiment of BBO-based localization is conducted. BBO-based algorithm is also stochastic, so, same solution is not expected in each trial even with initial identical deployment. This is the reason that average of total localization errors in (6) for all 30 trials is computed.
A. Comparison with PSO-Based Node Localization in WSN

The result of the proposed application of the algorithm is compared with the PSO-based node localization [15, 16]. It is observed from the simulation result that the proposed application of the algorithm has better localization accuracy and faster convergence than the PSO-based method. As scheme is stochastic, so, one can not anticipate the same solution in all trials even with initial identical deployment. That's why the results of 30 trial runs are averaged. Further, even though the initial deployment is also random but is preserved to be the same for all the two algorithms, so even then due to stochastic nature of algorithms, so even then due to stochastic nature of the algorithms, the number of localizable nodes in each trial is not expected to be the same, which makes the total computing time variable.

It is observed from Table 1 that performance of the algorithm depends upon the Gaussian noise level. As the Gaussian noise variance is low, the mean localization error EL is low. Hence, number of localized nodes is more. It can be observed from Table 1 that the proposed application BBO gives better accuracy as compared to the PSO than even the HPSO, however, convergence is significantly slower than that for PSO. A choice between PSO and BBO is dependent upon the requirement of accuracy or the fast convergence.

<table>
<thead>
<tr>
<th>SAs</th>
<th>$\sigma_d^2 = 8$</th>
<th>$\sigma_d^2 = 6$</th>
<th>$\sigma_d^2 = 2$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean of No. of un-localized nodes (N_{NL})</td>
<td>Mean Error (E_L)</td>
<td>Total Computing Time (sec)</td>
</tr>
<tr>
<td>PSO</td>
<td>2.0624</td>
<td>0.05046</td>
<td>86.007</td>
</tr>
<tr>
<td>BBO</td>
<td>1.657</td>
<td>0.02694</td>
<td>98.746</td>
</tr>
</tbody>
</table>

Table 1: Simulation results of thirty trial runs for comparison of PSO-based and BBO-based 3D node localizations

6. Conclusions and Future Scope

In this paper, stochastic range-based, single-hop and distributed node localization scheme by using the application of BBO has been presented. The proposed application of the algorithm has better accuracy in highly noisy (due to radio irregular model, i.e., DOI other than 1 and noise variance) environment. BBO-based localization algorithm finds the coordinates of the nodes more accurately. The choice between the two algorithms depends upon the trade-off between accuracy and the fast convergence. Further, the proposed algorithm may be implemented for range-free localization and a comparison can be made for energy awareness. A hybrid stochastic algorithm may be proposed to achieve both more accuracy and faster convergence.

References