LOCALIZATION OF UNDERWATER SENSOR NODE USING THE CUCKOO SEARCH ALGORITHM

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Abstract

In the underwater sensor network, the accurate position of every sensor node is of prime importance and the procedure of finding the node coordinates is known as localization. Localization plays a vital role in the designing and functioning of any Underwater Sensor Network (UWSN). Cheng et al.(III) prove effective localization algorithm has a greater influence on the performance of the network. Recent research exists in the field of exploring meta-heuristic based localization algorithms for effective sensor node localization by Kulkarni et al. (XI), and Kumar et al.(XII). The research contributions of Li & Wang (XIII), Goyal S Patterh & MS (VII) have proved that the cuckoo search (CS) algorithm is comparatively effective because of its distinctiveness of few parameters thus dropping the computational complication and communication overhead. CS has also proved to have better proficient global-search capability than the other well known optimization algorithms.

Keywords : Sensor, node, network, underwater, search, cuckoo.

I. Introduction

UWSN can be defined as a group of autonomous sensing nodes that are spatially distributed in the aquatic environment to sense various water-related properties. The sensed information is transmitted to the offshore remote stations for further processing of the data. UWSN has driven greater attention in the research field due to its applications like underwater surveillance, pollution monitoring, disaster prevention, assisted navigation, and exploration of oceanic resources.
Although numerous localization algorithms exist in the terrestrial Wireless Sensor Network (WSN), they cannot be applied in the UWSN, due to the unique characteristics of the aquatic environment. The most common and the simplest method for localization is by utilizing a Global Positioning System (GPS) system. But GPS does not function in the UWSN, as the radio signals cannot pass deep inside the water. Localization of sensor nodes is considered one of the most important challenges in UWSN as suggested in Han G et al, (VIII) and Han G et al, (IX). The current challenges faced in the localization algorithms have been studied. This paper explores the areas of nature-inspired meta-heuristic based algorithms for effective localization of sensor nodes.

II. Metaheuristic Algorithms

Stochastic algorithms are classified as heuristic and metaheuristic based algorithms. Heuristic algorithms explore solutions using trial and error approaches. Quality solutions are possible using this approach in a sensible amount of time, but it is not proven so far that optimal solutions could be achieved. Whereas the meta-heuristic based algorithm aims to find a reasonable solution in an adequate timescale. In Arora, S & Singh, S (II) and Harikrishnan et al. (X) the nature-inspired meta-heuristics projects heuristic methods inspired by nature that has enabled the survivability of insects, animals, and birds over the years by finding the perfect solution in every day to day activities like food, breeding, etc., (XVI). Many novel approaches and applications are emerging by utilizing these nature-inspired algorithms. The two most important ingredient of any metaheuristic algorithms is intensification, and diversification (IV). The former concentrates on the formulation of various solutions to investigate search space in the local region, whereas the latter focus on the search in the global space. A good mixture of these two essential ingredients would greatly achieve good optimality.

III. Cuckoo Search Algorithm

The renowned Cuckoo Search (CS) algorithm was initially proposed by Yang & Deb (VXI) is an algorithm that got its roots from nature, from the reproductive strategy of cuckoo birds in order to have a high population (XIV). This is one of the most sorted out nature-inspired algorithms selected for the optimization problems. When compared with other nature-inspired algorithms like Differential evolution (DE), Simulated Annealing (SA), and Particle Swarm Optimization (PSO), CS yields better results and has even outperformed other algorithms. Solihin & Zanil (XV) proved that the CS algorithm can yield better convergence speed to reach the optimum solutions in comparison with the DE algorithm. In addition, the CS algorithm has been recorded computationally more efficient than the PSO by Adnan & Razzaque(I).

Cuckoo Breeding Behaviour

The unique characteristics of cuckoo bird are its breeding behaviour, they usually lay their eggs in another host’s nest and also discard the host’s egg if any to increase the hatching capacity of its eggs. When host bird guesses the eggs are not its
kind, they would maximum discard them by laying them off or would choose to find a new nest for its own. This approach is used in CS algorithm by discarding the worst solutions after every iteration. The three key operators involved in the cuckoo search algorithms are briefed below:

**Crossover:** Process of mating two parents to produce new offspring or solution.

**Selection:** Process of selecting the highest quality solution or survival of the fittest among the population.

**Mutation:** Process of randomly changing the part of a chromosome to generate new characteristics, mostly done by flipping the value of one or more bits to arrive at an optimal solution. The mutation factor of CS algorithm varies concerning to the levy-flight. The fitness value is directly proportional to the generation of new solutions based on similarity to provide a subtle form of crossover. In addition, selection is carried out by using $p_a$, where the best solutions are passed on to the next generation, whereas the worst solution is replaced by new solutions. The general structure for the CS algorithm with these three key operators is illustrated in Figure 1.

**Levy Flights**

In general animals and birds randomly search for their food and when noted the foraging path of an animal is effective because the next direction of movement is decided by the current location or state. The direction of selection depends implicitly on a probability-based on the mathematical model. For instance,

\[ \text{Levy} \sim 1 - \beta \quad (1) \]

the previous reviews show us that the general pattern of animals has indicated the pattern of Levy flights. This when viewed under a broader perspective, the levy flight is a random walk whose s. Step length is drawn from the Levy distribution and is indicated as a simple power-law formula in eqn. (1).

**Fig. 1:** General Structure of CS Algorithm.
As this method is considered to be more efficient than most random walk based randomization techniques, CS is considered more efficient in the global search scenario. The CS algorithm considers three main conditions (Yang & Deb 2009):

- Every cuckoo bird lay only one egg at a instance and lays them in a nest chosen in a random fashion.
- The nest that was able to survive the eggs becomes the best nest and would be carried onto the subsequent generations.
- The host bird finds the cuckoo’s egg with a probability \( p_a \in [0, 1] \) and decides whether to discard the eggs and it leaves the nest and construct another nest.

IV. **Multilateration Method**

Multilateration method has been chosen for the measurement of the distance to achieve high localization accuracy. The multilateration method is best suited for calculating the coordinates of the ordinary nodes. Let us consider A, B, and C as the vertices of a regular tetrahedron. Let ‘a’ be the side of the equilateral triangle, which is the base triangle of the tetrahedron. Their coordinates of A,B,C are defined as \( x_1, y_1, z_1 \) is \((0,0,0)\), \( x_2, y_2, z_2 \) is \((\sqrt{3}/2,a/2,0)\) and \( x_3, y_3, z_3 \) is \((0,a,0)\). The method of finding D from A,B, and C is

\[
\begin{align*}
    x_4 &= \frac{x_1 + x_2 + x_3}{3} = \sqrt{3}/6a \\
    y_4 &= \frac{y_1 + y_2 + y_3}{3} = a/2 \\
    z_4 &= \text{height of the tetrahedron} = \sqrt{6}/3a \quad \text{(by formula)}
\end{align*}
\]

Therefore the coordinates of the point D are \((\sqrt{3}/6a,a/2,\sqrt{6}/3a)\). Let P be any point on the space and \( d \) is the distance between point P and any point on the vertices. Therefore \( d_1 \) is the distance between P and A=PA, \( d_2 \) is the distance between P and B=PB, \( d_3 \) is the distance between P and C=PC and \( d_4 \) is the distance between P and D=PD. Assuming the side of the equilateral triangle, \( a = 2 \), then the computation of \( P(x,y,z) \) derived from Priyadharsini et al (2017) is:

\[
\begin{align*}
    &A(0,0,0); B(\sqrt{3},1,0); C(0,2,0); D\left(\frac{1}{\sqrt{3}},1,\frac{2}{3\sqrt{6}}\right) \\
    &\left(PA^2\right) = (0-x)^2 + (0-y)^2 + (0-z)^2 = d_1^2 \\
    &= x^2 + y^2 + z^2 = d_1^2
\end{align*}
\]
\[ (PB^2) = (\sqrt{3} - x)^2 + (1 - y)^2 + (0 - z)^2 = d_1^2 \Rightarrow x^2 + y^2 + z^2 + 3 - 2\sqrt{3}x + 2y \] (7)
\[ (PC^2) = (0 - x)^2 + (2 - y)^2 + (0 - z)^2 = d_2^2 \Rightarrow x^2 + y^2 + z^2 - 4y + 4 \] (8)
\[ (PB^3) = \left(\frac{1}{\sqrt{3}} - x\right)^2 + (1 - y)^2 + \left(\frac{2}{3\sqrt{6}} - z\right)^2 = d_3^2 \Rightarrow \frac{2}{\sqrt{3}}x + 2y + \frac{4}{3\sqrt{6}}z = 4 + d_4^2 - d_3^2 \] (9)

From Equation (8),
\[ y = \frac{d_1^2 - d_3^2 + 4}{4} \] (10)

From Equation (7)
\[ x = \frac{d_1^2 - 2d_2^2 + d_3^2 + 4}{4\sqrt{3}} \] (11)

From Equation (9)
\[ z = \frac{d_1^2 + d_2^2 + d_3^2 - 3d_4^2 + 4}{4\sqrt{6}} \] (12)

Equations (10)-(12), are used to derive the values of \( P(x, y, z) \). The generation of the possible values of \( P(x, y, z) \) within the vertices of the regular tetrahedron can be achieved by substituting all possible values for the distance \( d_1, d_2, d_3 \) and \( d_4 \). Thus the values for these distance \( d_1, d_2, d_3 \) and \( d_4 \) are assumed from 0.1 to the assumed base of the triangle, ‘a’ in step size of 0.1.

V. Proposed Localization Method Using the CS Algorithm

The primary goal of this work is to obtain the localization of underwater sensor nodes by identifying the coordinates of the ordinary sensor for a UWSN. The proposed localization methodology using a cuckoo search algorithm is modified from Cheng J & Xia L(III), and is illustrated below and shown in Figure 2.

Step 1: Initially, all the sensor nodes, namely ‘M’ anchor nodes and ‘N’ unknown sensor nodes and R the transmission range are randomly deployed in the given area.

Step 2: Anchor nodes compute their position information and broadcast the same to the neighboring nodes at frequent intervals.

Step 3: The nodes that are within the transmission range of the four anchor nodes are localized and are identified as the new reference node.

Step 4: These reference nodes compute the distance from the anchor nodes using the multilateration.
method. $d_r = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2}$ \hspace{5cm} (13)

$d_r$ is the real distance, $d_c = d_r + N_{ij}$. $d_c$ is the computed distance and $N_{ij}$ is the ranging error between the unknown node and neighbouring anchor nodes.

**Fig. 2:** Flow of UWSN localization based on the Cuckoo search algorithm.
Step 5: Set the objective function, \( f(x) \) as,

\[
f(x_i, y_i, z_i) = \frac{1}{M} \sum_{j=1}^{M} (d_i - d_j)^2
\]

Step 6: To mitigate the effects of error and obtain the exact location information, every reference node initiates the CS algorithm. The pseudocode of the CS algorithm Yang & Deb (2009) is considered for evaluation.

Step 7: The obtained reference nodes are identified as the new anchor nodes in the successive iteration process.

Step 8: Repeat Steps 2 to 7 until all the unknown sensor nodes are localized. The number of localized nodes raises as the number of iterations raises.

Step 9: Compute the average localization error, \( LE \), and can be estimated using the equation given below in eqn.(15)

\[
LE = \sqrt{\frac{\sum_{i=1}^{N} \left( X_{a(i)} - X_{o(i)} \right)^2 + \left( Y_{a(i)} - Y_{o(i)} \right)^2 + \left( Z_{a(i)} - Z_{o(i)} \right)^2}{N}}
\]

Where \( X_{a(i)}, Y_{a(i)}, Z_{a(i)} \) specifies the real values of the x, y, and z coordinates of the sensor nodes and \( X_{o(i)}, Y_{o(i)}, Z_{o(i)} \) are the calculated values of x, y, and Z coordinates of the sensor nodes. \( N \) is the count of localized sensor nodes. The localization performance is directly proportional to the average localization error and will achieve greater localization success ratios with a decrease in the obtained average localization error.

VI. Experimental Results

The proposed algorithm is executed in MATLAB R2017a with Windows OS condition utilizing Intel Core i5 with 2.40 GHz, 4 GB RAM. The monitoring water space is a large regular truncated tetrahedron model with a volume of 50m × 50m × 50m. All the sensor nodes are deployed randomly in the given area.

The total number of sensor nodes varies from 50 to 200 in step size of 50. The anchor nodes are placed at the corner of the water surface within the given range. Anchor nodes are not considered in the evaluation of localization error and considered to be zero. The communication range of all the unknown sensor nodes is initialized in the range of 10 m~50 m.

The experimental results show that the proposed CS algorithm demonstrates higher localization precision with fewer iterations. Figure 4 shows the simulated results of the location estimation for 50 underwater sensor nodes. This shows the true location of the sensor nodes and the location estimated by the CS algorithm. The placement of the anchor node is one of the vital factors in deciding the localization.
success ratio. According to Doherty et al (V), the anchor nodes need to be placed at the edges and ideally at the corners of the selected network space.

The localization accuracy can be improved with a decrease in the calculated localization error. The localization error or the Root Mean Square Error (RMSE) is compared with other well known algorithms like Multidimensional Scaling-MAP (MDS-MAP) and Multi-stage Localization (MSL) discussed in Gao et al, (VI). Table 1 illustrates the root mean square error for different test cases and proves that our proposed approach of the CS algorithm shows better results in terms of the lower localization error.

Figure 5 illustrates the comparison of our approach with the other two algorithms in-terms of RMSE. It can be seen that the MDS-MAP and MSL have experienced an increase in error factor as the network size increases. Thus the modified CS algorithm, have purged this behaviour and ensures a low localization error factor.

![Fig. 4: Locations estimated by the Cuckoo Search algorithm for 50 underwater sensor nodes.](image)

Table 1: Estimated root mean square error for different test cases.

| Test Case | Node Density | RMSE         |
|-----------|--------------|--------------|
|           |              | CS | MDS MAP | MSL |
| 1         | 50           | 6.1191 | 15.7396 | 13.9396 |
| 2         | 100          | 5.923 | 15.98 | 13.98 |
| 3         | 150          | 5.789 | 16.2068 | 14.2068 |
| 4         | 200          | 5.5657 | 16.0747 | 14.8747 |

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The anchor density is another important factor leading to the localization success ratio and cost of the network. The anchor population is varied from 10% to 50%. The nominal anchor size could be chosen based on the need of the network. Figure 6 illustrates the comparison in terms of average localization against anchor node density error for different anchor ratio. It is obvious from the results that the localization error achieves a nearly steady localization error in terms of a larger network.

Fig. 5: Comparison of CS against existing algorithms in terms of RMSE for various network sizes.

Fig. 6: Average Localization error against anchor node density.
Figure 7 shows the Comparison in terms of average localization error for varying communication range of the sensor nodes. The communication range has also been varied from 10m to 50m in the simulated environment. The results show that, as the node density has reflected on an increase in the connectivity between the sensor nodes increased and reduces the localization error factor.

![Figure 7: Average Localization error against communication range](image)

**VII. Conclusion**

The localization problem is considered a multidimensional optimization problem and it is addressed through the metaheuristic approach using a Cuckoo search algorithm. CS is considered for the localization of underwater sensor nodes due to the fact that it involves few parameters for design and reduces the communication overhead to a large extend. The simulation result shows that CS has auto zooming ability, such that it can itself locate and identify the area where the promising global optimality is located. The proposed CS algorithm addresses the effects of parameters like anchor density, node density, and communication range concerning to average localization error and RMSE. The localization error is considerably reduced when compared with other known algorithms, under different test cases.
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