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Improved Grey Wolf Optimization Based Node Localization Approach in Underwater Wireless Sensor Networks

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Abstract: Underwater Wireless Sensor Networks (UWSNs) are established by Autonomous Underwater Vehicles (AUVs) or static Sensor Nodes (SN) that collect and transmit information over the underwater environment. Localization plays a vital role in the effective deployment, navigation and coordination of these nodes for many applications, namely underwater surveillance, underwater exploration, oceanographic data collection and environmental monitoring. Due to the unique characteristics of underwater transmission and acquisition, this is a fundamental challenge in underwater networks. However, localization in UWSNs is problematic due to the unique features of underwater transmission and the harsh underwater environment. To address these challenges, this paper presents an Improved Grey Wolf Optimization Based Node Localization Approach in UWSN (IGWONL-UWSN) technique. The presented IGWONL-UWSN technique is inspired by the hunting behavior of grey wolves with the Dimension Learning-based Hunting (DLH) search process. The proposed IGWONL-UWSN technique uses the Improved Grey Wolf Optimization Based (IGWO) algorithm to calculate the optimal location of the nodes in the UWSN. Moreover, the IGWONL-UWSN technique incorporates the DLH search process to improve the convergence and accuracy. The simulation results of the IGWONL-UWSN technique are validated using a set of performance measures. The simulation results show the improvements of the IGWONL-UWSN method over other approaches with respect to various metrics.

Keywords: Underwater Wireless Sensor Networks (UWSN), localization, sensor nodes, Grey Wolf Optimizer (GWO), localization accuracy.

1. Introduction

The concept of Underwater Wireless Sensor Networks (UWSNs) has attracted a lot of attention recently. Underwater Sensor Networks (USNs) can be used for a range of applications. Each implementation is critical in its field [1], but some could enhance ocean exploration to fulfill the number of underwater applications, namely, assisted navigation, natural disaster warning systems (e.g., seismic and tsunami tracking), ecological applications (e.g., pollution tracking, biological water quality), underwater monitoring, industrial applications (e.g., marine research), oceanographic information collection, and so on [2]. For offshore engineering applications, for example, sensors could evaluate a number of parameters, namely, mooring tension and base intensity, to monitor the structural quality of the mooring environment [3]. In addition to the essential features of typical Wireless Sensor Networks (WSNs), such as limited energy and large-scale deployment, UWSNs have certain differences from terrestrial systems. First, underwater transmission was detected only by the acoustic signal, which has higher error rates and lower bandwidth [4]. In addition, beacon nodes are sparser and the scale of node deployment in an underwater environment is very large. Non-negligible node mobility can lead to general fluctuations in the network topology due to water currents [5]. The tracking and detection of the intrusion object should rely on the location of the nodes in the marine military defense field [6].

Localization is a problem of estimating node locations and can be done globally using altitude, latitude and longitude data or locally using position data with respect to other nodes [7]. Location data is required for data tagging because the data received from the sink node cannot be recognized without node location information and becomes worthless for the application. Nodes with location data are called beacon or Anchor Nodes (ANs), while nodes without location data are called ordinary or blind nodes [8]. Furthermore, localization may be required not only for tagging objects, but also for finding the best routes in geographic routing and for optimal coverage of an area. Location information can be used to develop effective management and networking protocols [9]. The nodes can be deployed using an Autonomous Underwater Vehicle (AUV) or manually, depending on the area and network size. In manual deployment, the network is accessible to humans and the nodes register their location [10].

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2. RELATED WORKS

A mobile AN-based Received Signal Strength Indicator (RSSI) localization method in UWSN is presented in [11]. A Support Vector Regression (SVR) related to the interpolation approach was developed to predict the prediction of Sensor Nodes (SNs) on the linear trajectory of mobile ANs. Next, a curve matching approach was developed to determine the perpendicular distances of SNs to the linear trajectory of the mobile ANs. Finally, the simulation results prove that the presented method enables more precise SN localization in less time than the current methods.

A Cross-Layer Protocol with Lower Interference (CLIC) and congestion depending on directional reception is presented in [12]. In the CLIC method, a combined routing-MAC model can be developed to utilize the directional beams for creating high capacity and low interference data transmission links and balance the main aspects affecting the network performance to obtain low congestion and low collision routes. A Geodesic Search Algorithm (GSA) is related to target localization that minimizes the Localization Error (LE) using the phase-space constancy of the UWSN to efficiently triangulate the targeted nodes regardless of their mobility. A malicious AN approach was introduced in [13].

A better localization approach for mobile aquaculture WSN related to the Improving Dynamic Population Monte Carlo Localization (I-DPMCL) method is presented in [14]. According to these localization behaviors, specific delays were predicted depending on the statistical point of view. A performance comparison of I-DPMCL with other Sliding Mode Control (SMC)-related methods was also presented. In [15], a precise range-based method was modeled and the need to utilize the power of SNs expeditiously is a different feature of underwater WSNs. An improved analysis for underwater localization is developed by providing a general localization approach and then installing a normal beacon node to determine the accuracy and error of sensor localization. The author presented two localization methods, the angle-based method and the distance-based method.

A range-free Radial Basis Function Network (RBFN) and a Kalman Filtering (KF) based technique called RBFN+KF is presented. Compared to other techniques, the simulation results show lower location estimation errors [16]. Moreover, the RBFN-oriented approach is more energy-efficient than Multilayer Perceptron (MLP)-based localization and trilateration methods. An energy-free Heuristic Neural Network (HNN) localization method with Deep Learning (DL) algorithm for locating the dead Mobile Sensor Nodes (MSN) in a largescale Underwater Acoustic Sensor Network (UASN) is presented. The HNN localization achieves high accuracy and minimum LE compared to the presented DL algorithms [17].

The problem of localization in the UWSNs poses a great challenge due to the unique characteristics of underwater transmission and the harsh underwater environment. Conventional localization techniques often struggle to provide accurate and efficient localization solutions under such conditions. To overcome these challenges, this paper proposes an Improved Grey Wolf Optimization Based Node Localization Approach in UWSNs (IGWONL-UWSN) method.

3. PROPOSED SYSTEM

In this paper, we present a novel IGWONL-UWSN technique to determine the optimal location of SNs in the UWSN. The presented IGWONL-UWSN technique is inspired by the hunting behavior of grey wolves with the Dimension Learning-based Hunting (DLH) search process. The proposed IGWONL-UWSN technique utilizes the IGWO algorithm to calculate the optimal location of nodes in the UWSN. Fig. 1 shows the working procedure of the IGWONL-UWSN method, which employs UWSN with n nodes used in the 2D space of Z^2, and m ANs. There are $n-m$ unknown nodes. where $m<n$. The distance of all nodes to their near neighbors within their ranging distance was evaluated and then a network was used. All effective distance measurements are transmitted to the Base Station (BS) together with the node conditions using multi-hop routing. A graph is created and each evaluated distance is transmitted to the BS. This graph for WSN is modeled as G with (V,E), where V and E denote the group of vertices and edges. A group of SNs is denoted by the vertices V with $\{v_1,v_2,..v_n\}$. The connection of vertices is denoted as a group of edges E with $\{e_{1,2},e_{1,3},..e_{i,j},..e_{n-1,n}\}$. If the connected component of $G,G_1=(V_1,E_1)$ does not have three or more ANs, then any SN from the subgraph G_1 cannot be localizable. It assumes that each connected element of the graph G has at least 3 anchors.

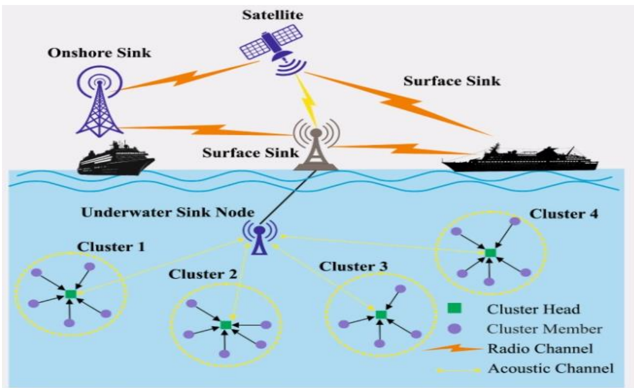

Fig. 1. Working process of the IGWONL-UWSN approach.

A. *Design of the Improved Grey Wolf Optimization Based (IGWO) algorithm*

The Greedy Wolf Optimization (GWO) algorithm is a Swarm Intelligence (SI) optimization technique in which the process of finding the global optimum is motivated by the hunting behavior of the Greedy Wolf (GW) population. There is a strict hierarchy in the GW population, and a few GWs with absolute discourse power guide a population of GWs towards the prey. GWs are usually divided into 4 groups: α, β, δ, and ω wolves. The rights are from larger to smaller to simulate the leadership class. Collective hunting is a social behavior of GWs. It mainly consists of three phases: (1) approaching, harassing and tracking the target; (2) encircling and hunting the prey until it stops moving; and (3) attacking the target. First, create a mathematical process for the social hierarchy of the GW and the model of the social hierarchy of GW. The α wolf is used as the optimal solution, i.e. the fitness of the individual is optimal, the suboptimal solution is the β wolf, and the fittest solution is the δ wolf, i.e. the global optimum or the local optimum solution of the main function, with the minimum or maximum values of the main function. The remaining candidate solution is called the ω wolf. The hunting strategy is based on the β, δ, and ω wolves following the above three wolves. More specifically, look for the three best solutions first and then search around the area to find the best solution and improve the β and δ wolves later. The GW strategy of prey hunting can be described using (1):

$$D = \left| C \cdot X_p(z) - X(z) \right| \tag{1}$$

The equation for the position update of GW is given below:

$$X(z+1) = X_p(z) - A \cdot D \tag{2}$$

Coefficient vector:

$$A = 2\alpha \cdot r_1 - \alpha \tag{3}$$

$$C = 2 \cdot r_2 \tag{4}$$

From the equation, X_p stands for the vector prey location, X represents the place vector of the GWs, z denotes the number of iterations, D shows the distance vector between the individuals and the hunt, r_1 and r_2 are the random vector numbers from the interval of zero and one and α denotes the convergence factor (decreases linearly in two to zero with the iteration number).

GWs could find the location of the prey and encircle it. Once the GW has identified the location of the prey, it leads the wolf population to encircle the prey in the guidance of β and δ. The tracking of the prey location can be mathematically modeled as follows:

$$D_\alpha = |C_1 \cdot X_\alpha - X|$$

$$D_\beta = |C_2 \cdot X_\beta - X| \tag{5}$$

$$D_\delta = |C_3 \cdot X_\delta - X|$$

From the expression, D_α, D_β and D_δ signify α, β and δ and the distance to other individuals, respectively; X_α, X_β and X_δ show the existing location of α, β and δ, respectively; C_1, C_2 and C_3 represent a random vector and X indicates the existing location of the GW. Equation (6) determines the step length and direction of ω individuals from the wolf pack near α, β and δ, and (7) describes the final location of ω. The steps of GWO are shown in Fig. 2.

$$X_1 = X_\alpha - A_1 \cdot (D_\alpha)$$

$$X_2 = X_\beta - A_2 \cdot (D_\beta) \tag{6}$$

$$X_3 = X_\delta - A_3 \cdot (D_\delta)$$

$$X_{z+1} = \frac{X_1 + X_2 + X_3}{3} \tag{7}$$

B. Process involved in the IGWONL-UWSN technique

The proposed IGWONL-UWSN technique utilizes the IGWO algorithm to calculate the optimal location of nodes in the UWSN. The goal of IGWONL-UWSN localization in a UWSN is to find the coordinates of $n - m$ unknown nodes and use the previous data about the locations of m ANs. The presented main function for node localization contains 2 phase processes. The primary one is a ranging system in which the nodes determine their distances in ANs based on the signal propagation time or RSSI, and the secondary one is the position estimation of the nodes, i.e. using the ranging data. The LE was minimized by applying optimization techniques. Initially, all ANs in the application estimate their distance to each of their neighboring target nodes. RSSI ranging technology is used to determine the distance between the nodes.

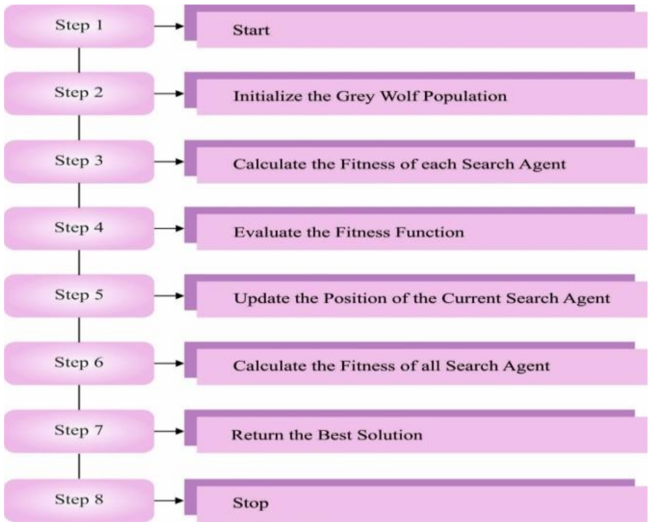

Fig. 2. Steps involved in GWO.

The distance between the unknown nodes $o(x, y)$ is denoted as d_1, d_2, d_n and AN was obtained by the hop count and the average hop distance between the nodes. The ranging error is $\varepsilon_1, \varepsilon_2, \varepsilon_n$, the estimation coordinates (x, y) satisfy the following inequalities:

$$\begin{cases} d_1^2 - \varepsilon_{1^2} < (x - x_1)^2 + (y - y_2)^2 \leq d_1^2 + \varepsilon_{1^2} \\ d_2^2 - \varepsilon_{2^2} < (x - x_2)^2 + (y - y_2)^2 \leq d_2^2 + \varepsilon_{2^2} \\ \qquad\qquad\qquad \cdots\cdots \\ \qquad\qquad\qquad \cdots\cdots \\ d_n^2 - \varepsilon_n^2 < (x - x_n)^2 + (y - y_n)^2 \leq d_n^2 + \varepsilon_n^2 \end{cases} \tag{8}$$

where d refers to the actual distance between 2 nodes and ε denotes the ranging error. The localization problem has been changed to searching for coordinates (x, y) that minimize the objective function $f(x, y)$. This optimizer $f(x, y)$ guarantees minimum total error.

$$f_{(x,y)} = \sum_{j=1}^{m} \sum_{i=m+1}^{n} \left| \sqrt{\left((x_i - x_j)^2 + (y_i - y_j)^2\right)} - d_j \right| \quad (9)$$

where (x_i, y_i) and (x_j, y_j) are the coordinates of the locations of nodes i and j. d_j denotes the distance between unknown nodes to AN j.

4. RESULTS AND DISCUSSION

In this section, the simulation results of the IGWONL-UWSN method are examined in detail. Fig. 3 shows a comparison of the IGWONL-UWSN system in terms of the number of Localized Nodes (LN) under different anchors. The results show that the IGWONL-UWSN method achieves higher LN values. For example, on 10 anchors, the IGWONL-UWSN system achieves a superior LN value of 163, while the Smell Sensing (SS)-Differential Evolution (DE), SS-Network Lifetime (NL), Cuckoo Search (CS)-NL and GWO-NL techniques achieve a lower LN value of 142, 139, 128 and 119, respectively. On 50 anchors, the IGWONL-UWSN approach achieves an improved NL value of 198, while the SS-DE, SS-NL, CS-NL and GWO-NL systems achieve a lower LN value of 182, 177, 165 and 147, respectively.

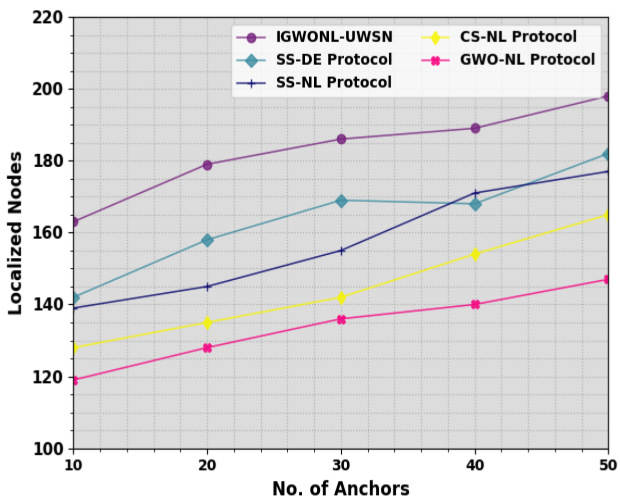

Fig. 3. LN analysis of the IGWONL-UWSN approach under distinct anchors.

A detailed LE assessment of the IGWONL-UWSN method compared to other systems under distinct number of anchors can be found in Fig. 4. The simulation values show that the IGWONL-UWSN method resulted in improved performance with lower LE values. On 10 anchors, the IGWONL-UWSN method achieves better performance with a minimum LE value of 0.181, while the SS-DE, SS-NL, CS-NL and GWO-NL approaches achieve higher LE values of 0.319, 0.461, 0.477 and 0.563, respectively. At the same time, the IGWONL-UWSN system achieves optimal performance on 50 anchors with a lower LE value of 0.053, while the SS-DE, SS-NL, CS-NL and GWO-NL methods achieve maximum LE values of 0.281, 0.344, 0.356 and 0.445, respectively.

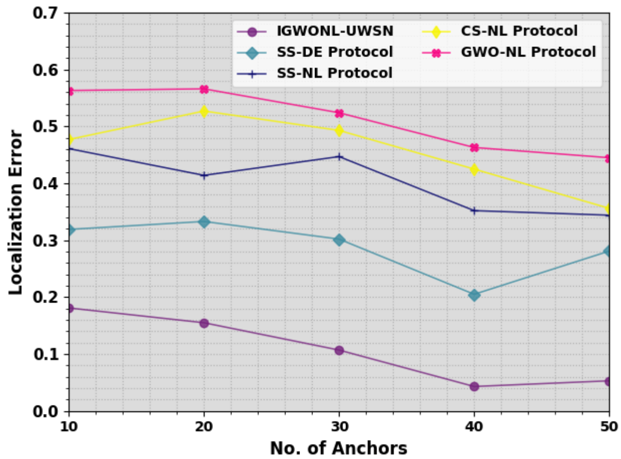

Fig. 4. LE analysis of the IGWONL-UWSN approach under distinct anchors.

A comprehensive LE result of the IGWONL-UWSN technique with other methods under distinct transmission ranges. The simulation values show that the IGWONL-UWSN method has resulted in improved performance with minimum LE values. At a 10 m transmission range, the IGWONL-UWSN technique achieves better performance with a minimum LE value of 0.134, while the SS-DE, SS-NL, CS-NL and GWO-NL approaches achieve higher LE values of 0.205, 0.286, 0.397 and 0.518, respectively. At the same time, the IGWONL-UWSN system achieves the best performance at a 30 m transmission range with a minimum LE value of 0.016, while the SS-DE, SS-NL, CS-NL and GWO-NL methods achieve the maximum value.

The computational complexity of IGWONL-UWSN is balanced against its performance in terms of localization accuracy. While the GWO algorithm used in IGWONL-UWSN may require computational resources, especially for large-scale networks, it has the advantage of optimizing the node coordinates to efficiently minimize the LE. The trade-offs between computational complexity and performance depend on factors such as network size, environmental conditions and the desired localization accuracy. Therefore, it is important to evaluate the computational requirements of IGWONL-UWSN in relation to its localization performance to achieve an optimal balance.

5. CONCLUSION

In this paper, we have developed a new IGWONL-UWSN algorithm to determine the optimal location of SNs in the UWSN. The presented IGWONL-UWSN technique is inspired by the hunting behavior of grey wolves with the DLH search process. The proposed IGWONL-UWSN technique utilizes the IGWO algorithm to calculate the optimal location of the nodes in the UWSN. In addition, the IGWONL-UWSN technique incorporates the DLH search process for greater convergence and accuracy. The simulation results of the IGWONL-UWSN technique are validated using a set of performance measures. The simulation results illustrate the developments of the IGWONL-UWSN method over other systems in terms of various metrics. In the future, node mobility can be considered in the development of the IGWONL-UWSN technique in the UWSN. Future directions in this area could include the development of adaptive algorithms capable of adapting to changing environmental conditions, the integration of machine learning techniques to improve localization accuracy, and the exploration of applications in emerging areas such as underwater robotics and autonomous systems.

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