Journal of Advances in Computer Research
Quarterly pISSN: 2345-606x eISSN: 2345-6078
Sari Branch, Islamic Azad University, Sari, I.R.Iran
(Vol. 10, No. 2, May 2019), Pages: 91-107
www.jacr.iausari.ac.ir

Localization of Underwater Wireless Sensor Network Nodes Using Cuckoo Optimization Algorithm

Leila Falahatpisheh✉
Department of Information and Communication Technology, Babol, Iran
la.falahatpishe@tci.ir

Manuscript ID: JACR-1903-1663 **Received: 2019/03/16; Accepted: 2019/09/26**

Abstract

Underwater Wireless Sensor Networks (UWSNs) are considered as wireless sensor networks whose main task is to sense underwater events and send information to the sink. This information becomes valuable when the exact location of the occurrence is known. Generally, underwater sensor nodes are not equipped with devices such as the Global Position System (GPS) with the purpose of reducing network costs. Therefore, finding the location of the nodes should be done using another exact method. In this paper, we intend to find the location of the underwater sensor nodes by introducing a new method based on the Cuckoo Optimization Algorithm (COA). We will compare the proposed method with the related methods in terms of the localization error rate and the number of nodes discovered. The results of the comparisons show that the proposed method can greatly reduce the error rate of the localization of the sensor nodes.

Keywords: *Localization Sensor, Underwater Wireless Sensor Networks, Cuckoo Optimization Algorithm, Triangular Method*

1. Introduction

The advancements in the field of wireless telecommunications have made it possible to build sensors in small sizes with low power consumption and reasonable prices. These sensors have led to the emergence of networks known as wireless sensor networks. Wireless sensor networks can be used in industry, agriculture, and military environments. Underwater wireless sensor networks are a kind of sensor networks that are used underwater to collect environmental data. Underwater sensor networks have capabilities that increase human ability in exploratory applications. It is possible to establish wireless communications between two telecommunication devices underwater in three ways, namely electromagnetic waves, optical waves, and acoustic waves. The first two are not suitable due to underwater conditions. For this reason, the localization of underwater wireless sensor networks is performed using of acoustic modems [1].

Each type of wireless network has special challenges to face. For example, one of the most important challenges of Radio Frequency Identification (RFID) networks is the collision problem [2], and the Internet of Things (IoT) networks face the challenge of security [3]. The main challenges of wireless sensor networks on land are energy consumption and reliability. However, underwater wireless sensor networks have challenges like the localization of sensors (due to the possibility of displacing nodes underwater) and high cost.

In underwater sensor networks, the data collected by the nodes are processed according to their position. Reporting the occurrence of an event or monitoring physical conditions are among the applications in which the location of the desired event is critical [4]. Lack of knowledge of the location of a sensor causes the data collected by that sensor to fall into useless. In the sensor networks, the process of estimating the location of a node is called localization.

Today, the problem of localization and increasing the accuracy of localization has attracted the attention of researchers. The goal is to find the correct location of each node with the lowest cost. Localization is done with two methods, locally and globally. In the local method, the location of a node is measured relative to the location of the other nodes. In the global method, a tool such as GPS is used. In global methods, due to cost reduction, not all sensors are usually equipped with a GPS system. Sensors equipped with GPS are known as reference nodes and usually have more hardware power than other sensors. The coordinates of the remaining sensors in the global method are estimated using some reference nodes based localization techniques. One of the important issues regarding these techniques is determining the distance between a node and a reference node. For example, the distance estimation method based on the time of arrival or the received signal strength (RSS) determines the distance between a node and a reference node. In practice, due to the presence of noise, salinity, and concentration, the distance determines may have error. For example, if the actual distance between two nodes is 1000 meters, considering three percent noise will allow the distance between the two nodes to be estimated to be somewhere between 970 and 1030. In this paper, an optimization algorithm called the cuckoo optimization algorithm is used to locate sensors after estimating the distance between each sensor and the reference nodes. Research contribution are:

1-In this paper, an algorithm based on the cuckoo optimization algorithm was presented to locate sensors.

2- In the proposed method, with a low cost, we can localize sensors in an acceptable rate of error.

3- The proposed method has better results compared to other methods in presence of noise.

The remainder of this paper is organized as follows. Section 2 describes the related work. Section 3 discusses the cuckoo optimization algorithm and section 4 presents methodology. Section 5 explains the experiments performed and analyzes the results. Finally, Section 6 presents the concluding remarks and proposes future works.

2. Review of Literature

In this section, we will examine the methods and studies conducted with the aim of localizing the underwater wireless sensor networks. The basis of many localization techniques is estimating the distance between the two sensor nodes. The distance estimation method based on the time of arrival estimates the distance between the transmitter and the receiver based on the signal propagation speed. For example, the speed of an acoustic signal in an underwater environment is approximately 1500 m/s. It is possible to obtain an approximate distance by multiplying the time between sending and receiving the signal by the signal speed number. This method can be utilized in two forms, namely one-way and two-way. In the one-way method, node A sends the T_1 time stamp with the signal when sending it. Node B receives this signal in T_2 time stamp and performs Equation 1. Figure 1 shows the structure of this method.

$$Distance_{AB} = (T_2 - T_1) \times V \quad (1)$$

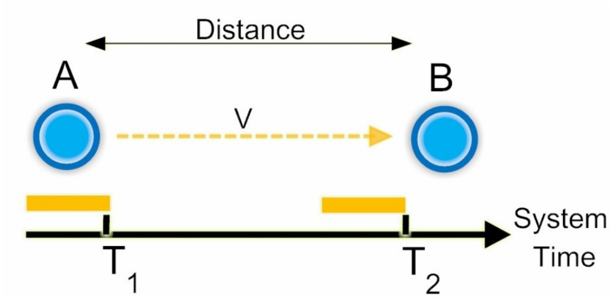

Figure 1. Calculating the distance using the one-way method

T_1 and T_2 are the times of sending and receiving signals and V is the signal speed. In the one-way method, the transmitter and receiver clock must be synchronous. Therefore, the two-way method is preferred. In the two-way method, the signal sweep time is calculated on the transmitter side. In the two-way method, the transmitter node estimates the distance to the receiver according to equation (2). Figure 2 shows the structure of the two-way method.

$$Distance_{AB} = \frac{(T_{A2} - T_{A1}) + (T_{B2} - T_{B1})}{2} \times V \quad (2)$$

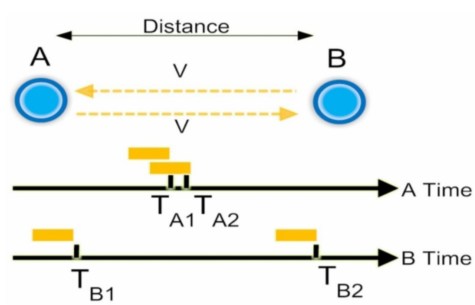

Figure 2. Calculating the distance using the two-way method

In the distance estimation method based on the Time Difference of Arrival (TDOA), two signals of different speeds are used. For example, the transmitter node can use the radio signal for its first broadcast and the acoustic signal for its second broadcast. The receiver node can calculate its distance to the transmitter node by receiving two signals using equation (3). Figure 3 shows the structure of this method.

$$Distance_{AB} = (T_{B2} - T_{B1}) \times V_2 \quad (3)$$

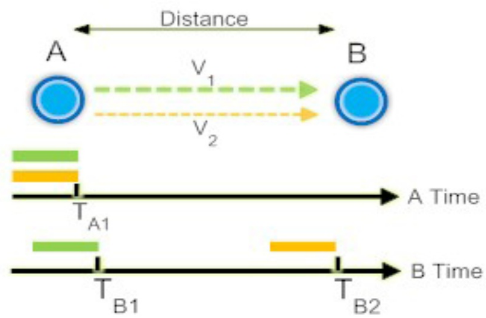

Figure 3. Calculating the distance using the TDOA method

Where V_1 is the speed of the first signal and V_2 is the speed of the second signal. The advantage of this method is the lack of need for the clock synchronicity of the two nodes and the disadvantage is the need for additional hardware for sending two different signals. This method is not very efficient due to the high signal attenuation in the underwater environment [5].

In the distance estimation method based on the received signal strength, the distance is measured based on the signal attenuation rate. The transmitted signal weakens in terms of power along the path between the transmitter and receiver. In this method, a piece of hardware called RSSI is used which can measure the amplitude of the input signal.

Yu et al. proposed a method called Triangular which uses mathematical formulas to locate nodes. In this method, the nodes estimate their distances from three reference nodes according to the TOA method. In an ideal and noise-free mode, the location of each unknown node is easily calculated using the trigonometric formulas. However, in practice, due to the presence of noise and error in the distance determination, a triangular area is considered as the presence area of an unknown node. Authors consider the center of gravity of this area as an unidentified node location [6].

Yahya and Ben-Othman proposed a GPS-less localization protocol that is a two-stage protocol based on the reference node signal. The system coordinates are determined once. The two-step search protocol needs to exchange a high volume of messages. In addition, the nodes should be static. It should also be noted that the dynamic nodes severely reduce the localization accuracy [7]. Mirza and Schirjers proposed a MSAL protocol related to the motion-aware sensor localization, which specifically describes the localization error resulting from distance estimation, which can occur due to node mobility [8]. Zhang et al. proposed a localization and synchronization algorithm for three-dimensional sensor networks. Three-dimensional networks are divided into cells, and localization is performed on cellular levels. Each usual node is qualified as a new reference node, and it is synchronized only when it receives beacons from 5 reference nodes [9]. Lloyd et al. proposed an AUV localization algorithm. The AUV moves through underwater sensor networks via aqueous flows at specified intervals. The AUV position is updated when it comes up to the water surface with the help of GPS and again goes deep into the predefined depth to perform the two-way message exchange for usual nodes at regular intervals. Each usual node can perform the localization as soon as it receives a successful two-way message from at least three AUVs [10]. Irol et al. proposed the Proxy Localization (PL) algorithm. In this protocol, to minimize the propagation error, the usual nodes that are localized can be selected as new reference nodes and send beacons [11]. In paper [12], the range-free scheme employs an AUV to periodically broadcast a message via four directional acoustic beams. Both AUV position and a directional dependent marker are contained in the message. The directional dependent marker is used to identify the respective transmit beam. As showed in Figure 4, the angles between the beams and the AUV body are fixed. The node receives the message and using the two different successive beams can obtain the location of the AUV at two different time instants. Then, utilizing the two estimated positions can obtain the position of the node.

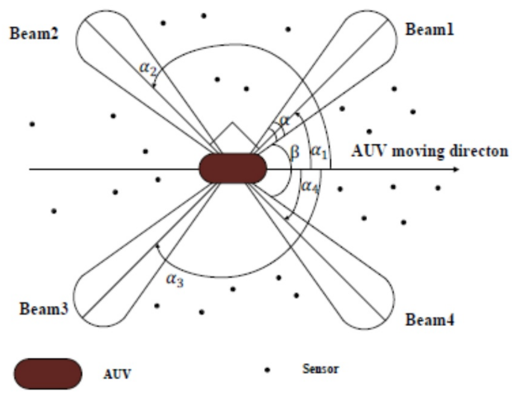

Figure 4. An AUV equipped with four directional beams

Meiqin et al. [13] discussed a spatial-correlation based distance mobility prediction. However, by adopting trilateration technique, localization service generates high communication overhead in the network. Zhang and Liang proposed a sensor localization method based on ranging technology of TOA and Improved PSO (particle swarm optimization) algorithm [18]. The authors used of new inertia weight and competition mechanism to improve the standard PSO algorithm.

The UOWSN localization technique was presented by Akhoundi et al. where the ToA and RSS methods are investigated in the case of an optical code division multiple access network [20].

An RSS-based localization technique was developed by Saeed et al., taking into consideration the outliers in ranging and optimizing the location of anchor nodes to improve the localization accuracy in UOWSNs. ToA-based localization schemes can provide higher precision, strongly relying on synchronization and additional clocks to measure the time of transmission, yielding to extra hardware complexity and cost. However, RSS-based localization schemes are generally preferred because of their simplicity and cost efficiency [21].

3. Cuckoo Optimization Algorithm

In today's complex issues, modern methods should be used. Many issues cannot be solved by traditional methods. The meta-heuristic algorithms can find the quasi-optimal solution to complex problems in a short time [14-16]. In this paper, we intend to use the cuckoo optimization algorithm to determine the location of each sensor node. The COA is one of the most powerful meta-heuristic algorithms inspired by the life of a bird named cuckoo. [19]

The COA algorithm starts its work with a primary population of cuckoos. This population of cuckoos has a number of eggs and puts them in the host birds' nests. A number of these eggs, which are more similar to the host bird eggs, will have a greater chance of growing and becoming mature cuckoos. Other eggs are identified and destroyed by the host bird. Whatever the more eggs are saved in an area, the more fitness is assigned to that area. Therefore, finding the position where the largest number of eggs survives is the goal of the COA algorithm. Cuckoos search to find the best region. After the chicken have hatched and become mature cuckoos, they form groups. Each group has its own habitat to live. All groups move toward the best available current region. Each group settles in an area close to the best current region. Regarding the number of eggs that each cuckoo lays, as well as the cuckoos distance from the optimal current region for habitation, an egg-laying radius (ELR) is calculated for each cuckoo. The cuckoos then begin to lay eggs randomly within their ELR. This process continues until it reaches the best place for laying eggs (the region with the highest profit) [17]. Figure 5 shows the flowchart of the COA.

3.1 Generation of initial population and cuckoos egg-laying

In the COA, each problem solution is called a habitat. If the problem has N dimensions, each habitat is denoted by an N-dimensional array. For each of these habitats, a number of eggs are considered randomly. In fact, each egg is the coordinates of a point in the problem space. In the nature, each cuckoo lays 5 to 20 eggs. These numbers are used as the upper and lower limits of the number of eggs per cuckoo in different iterations. Each cuckoo lays its eggs at a certain radius. The maximum egg-laying radius is called ELR. In an optimization problem with the upper limit var_{high} and the lower limit var_{low} for variables, each cuckoo will have an ELR. This value is proportional to the total number of eggs, the number of current cuckoo eggs, as well as the upper and lower limits of the problem variables. Therefore, the ELR value for each cuckoo is defined as equation (4).

$$ELR = \alpha \times \frac{Number\ of\ current\ cuckoos\ eggs}{Total\ Number\ of\ eggs} \times (Var_{high} - Var_{low}) \tag{4}$$

α is a control parameter that adjusts the maximum ELR value. Each cuckoo randomly lays eggs in a host birds nest located within its ELR radius. Figure 6 shows the randomized laying in the ELR radius.

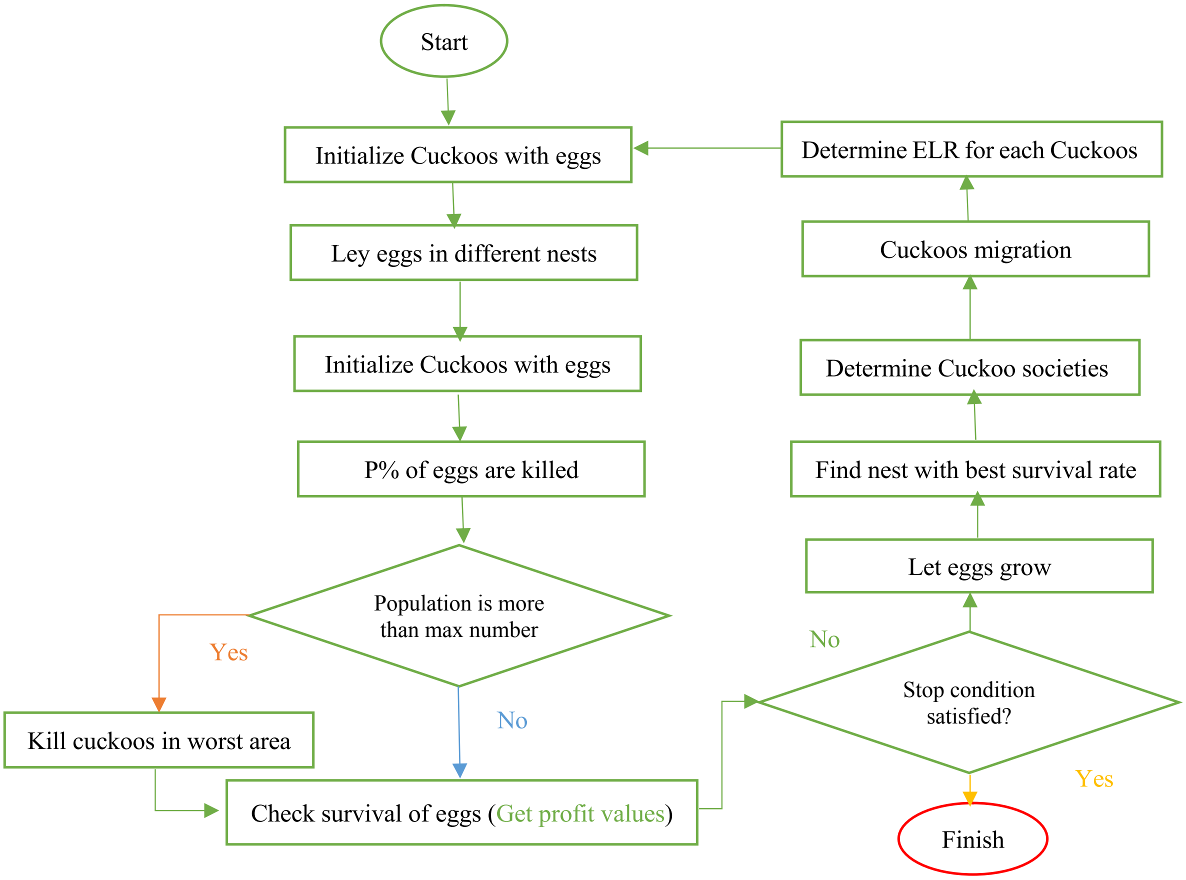

Figure 5. Flowchart cuckoo optimization algorithm

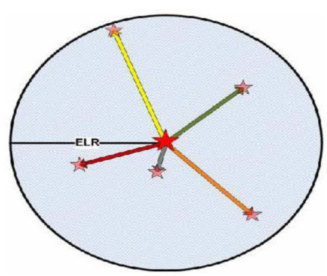

Figure 6. Random egg laying within the ELR radius; the central asterisk is the original cuckoo habitat, and the rest of the asterisks are new nests for the eggs

3.2 Migration of cuckoos

After the chickens have matured, they live in their environments and groups for a while, but when the laying time approaches, they migrate to better habitats where there is more chance of surviving eggs. Following the formation of cuckoo groups in the ecosystems (problem search space), the group with the best position is selected as the destination for other cuckoos to migrate to. After the cuckoo groups have formed, the average fitness of each group is calculated in order to obtain the optimality of each group's habitat. Then, the group with the highest average of fitness is selected as the target group and other groups migrate to it. When migrating toward the target point, cuckoos display random movements. This type of movement is shown in Figure 7 [17].

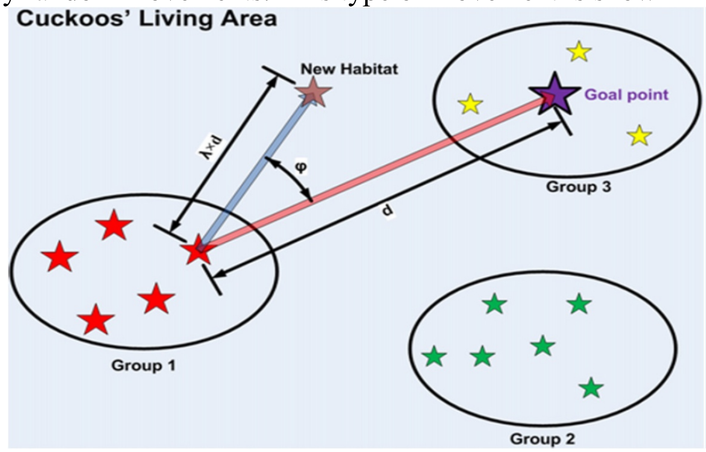

Figure 7. Migration of a cuckoo to the target habitat

As shown in the figure, each cuckoo only travels λ% of the entire path toward the current ideal target point and has a deviation of φ radians. These two parameters help the cuckoos search for more environment. λ is a random number between [0-1] and φ is a number between $\frac{\pi}{6}$ and $\frac{-\pi}{6}$. After all the cuckoos have migrated to the target point, each cuckoo will own a number of eggs. According to the number of eggs per cuckoo, an ELR radius value is determined for it, and then the laying begins. Given the fact that there is always an equilibrium between the populations of birds in the nature, a number such as $N_{\max}$ controls and limits the number of cuckoos that can possibly live in an environment. After several iterations, the entire cuckoo population reaches an optimal point. This place will have the most overall favorability according to which the least number of eggs is destroyed.

4. Methodology

Proposed method consist of two phases. In the first phase distance between sensor nodes and reference nodes will be determined. In the second phase, each sensor node that could receive at least three beacons from reference nodes run, COA algorithm to estimate its position.

4.1 Distance to reference nodes

As mentioned before in the case of the UWSNs, nodes are randomly distributed in an underwater environment. In each underwater sensor network, there are a number of nodes as reference nodes whose locations are predefined and constant. Each reference node has a fixed range for sending beacons. The value of this range is greater than that of the range of usual sensor nodes, but the range of usual nodes is the same and equal to R. The coordinates of reference nodes are known. The reference nodes notify their coordinates by sending beacons periodically for calculating the locations of unknown nodes. To find the location of a node, it is necessary to know the distance between the reference nodes and those nodes (unknown nodes). This problem can be solved with the aid of the signal TOA method. Provided that each usual node is within the range of receiving beacons from at least three reference nodes, it can estimate its position by determining its distance from the reference nodes and then executing the COA algorithm according to the flowchart shown in Figure 8. Figure 9 gives an example of a usual node placed within the range of receiving beacons from three reference nodes.

The distance between a sensor node and the i-th reference node is equal to d_i which is calculated based on the TOA method using equation (1).

4.2 Localization of sensor nodes using the cuckoo optimization algorithm

Each node that was within the range of receives beacons from at least three reference nodes, independently executes the COA algorithm in order to find the coordinates of its location. The target function in this algorithm is defined as equation (5).

$$F(x,y)=\frac{1}{m}\sum_{i=1}^{m}(d_i-\hat{d}_i)^2 \tag{5}$$

Where $\hat{d}_i$ is the distance between the cuckoo and the i-th reference node? Each solution in the population (each cuckoo and each egg) is a position (X, Y) in the problem space. Each cuckoo with a lower fitness function value can better estimate the sensor node coordinates. By performing iterations, the algorithm tries to find some coordinates at which the value of the fitness function is equal to zero. Each unknown sensor node within the range of receiving beacons from at least three reference nodes executes the COA algorithm. After the COA algorithm have been executed, that sensor node is no longer unknown and becomes a secondary reference node. From that moment on, these nodes known as secondary reference nodes and can send beacons within the R range. If a node can receive beacons from at least 3 reference nodes (whether primary or secondary), it can execute the COA algorithm and determine its own. If a node is located at a point in the problem space where it can never receive at least 3 beacons from the reference nodes, it remains unknown until the end. Finally, the average value of the known nodes localization error is calculated as the localization error of the algorithm according to the equation (6).

$$Error=\frac{1}{n}\sum_{i=1}^{n}\sqrt{(x_i-\hat{x}_i)^2+(y_i-\hat{y}_i)^2}\times 100 \tag{6}$$

This equation is based on the total average difference between the estimated location and the actual location of the sensor nodes. The number of known sensor nodes is denoted by n. The actual location of the i-th known sensor is (x_i, y_i) and the estimated location of the sensor is $(\hat{x}_i, \hat{y}_i)$. The lower the average error rate, the better the algorithm performance.

5. Experiments

The experiments were performed with the MATLAB software on a system with an Intel core i7, a 3.2 GHz processor, a 8GB RAM, and a 64-bit Windows 10 operating system. For simulate a number of sensor nodes are randomly distributed in an area of 1000 × 1000 square meters. Also, four fixed reference nodes are located in four corners of the area. The range of all usual sensors is equal to R=50 and the range of four reference nodes is equal to 1000 meters. Figure 10 shows the random distribution of 100 sensor nodes in the area.

To make comparisons, the PSO and IPSO algorithms introduced in the article [18] and the triangular method presented in the article [6] are used. As noted above, the main objective of the proposed method is to reduce the localization error. Table 1 shows the results of the localization error rate of the COA algorithm and other algorithms. Since metaheuristic algorithms are based on randomization, the average of the results of their 20 independent executions is shown in Table 1. The experiment performed on algorithms included a different number of sensors and 3% noise. For example, when 40 sensor nodes were randomly distributed in the area, the least amount of localization error was related to the COA algorithm with an average value of 12.52. The IPSO algorithm could perform better than the standard version of the PSO algorithm and localize the nodes with less error rate. Finally, the triangular method with the average error of 15.18 is in the last rank.

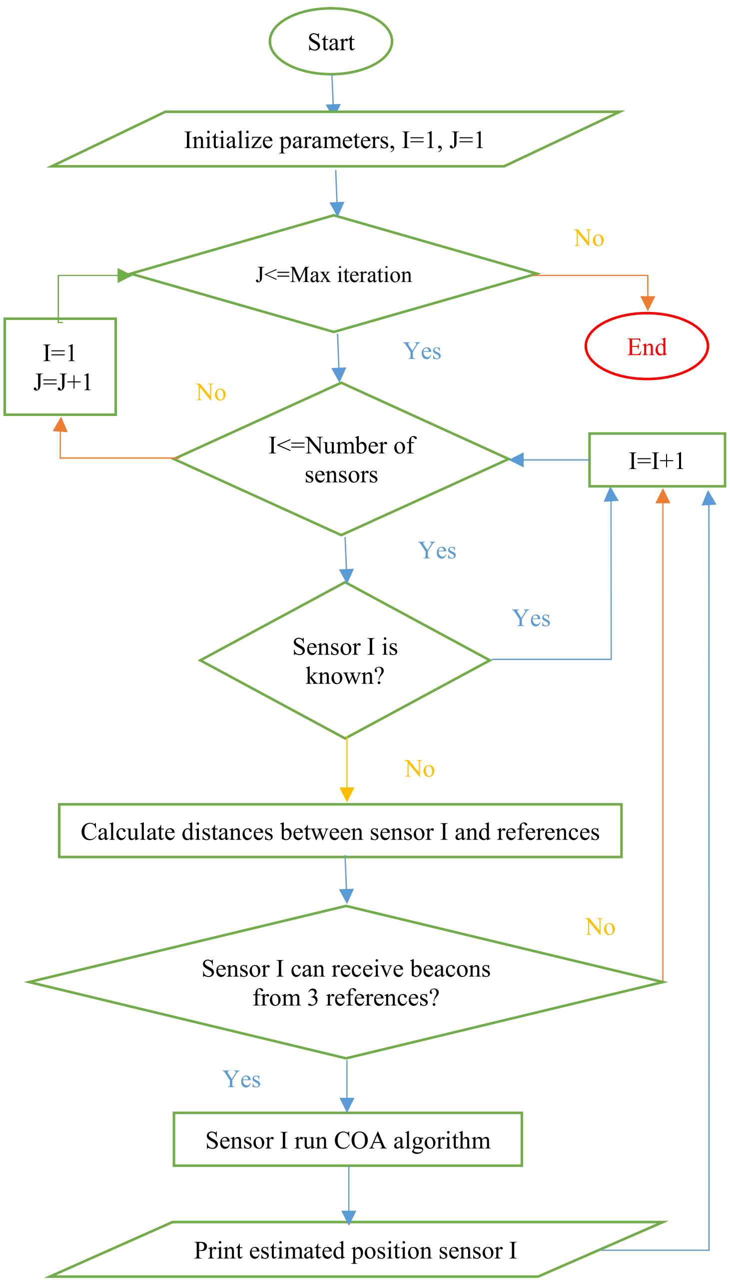

Figure 8. Flowchart proposed algorithm

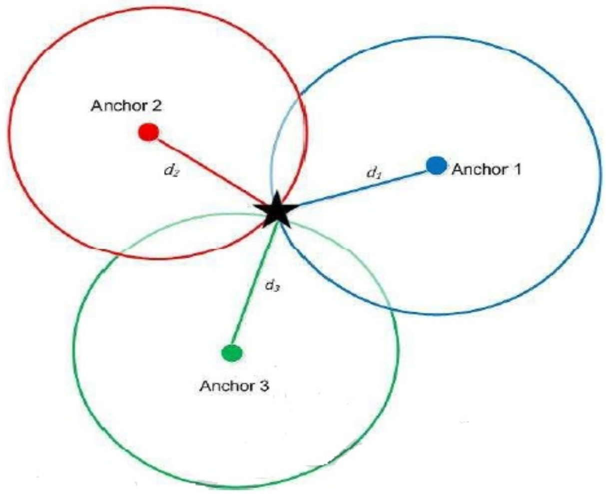

Figure 9. An example of a usual sensor node that receives beacons from three reference nodes

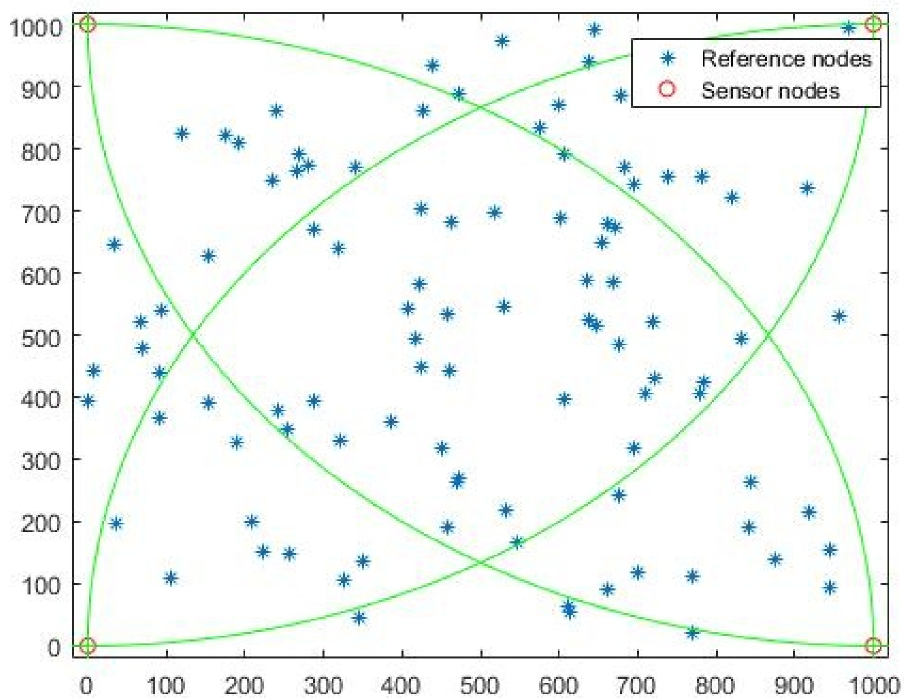

Figure 10. Random distribution of 100 sensor nodes in the area

Table 1. A comparison of the number of unknown nodes and the error rate of localizing algorithms

sensors	PSO Algorithm Errors	Unknown Sensors in algorithm PSO	Time (s)	IPSO Algorithm Errors	Unknown Sensors in algorithm IPSO	Time (s)	Algorithm Errors Triangular	Unknown Sensors in algorithm Triangular	Time (s)	Algorith m Errors COA	Unknown Sensors in algorithm COA	Time (s)
40	15.14	7.0	0.07	13.72	7.0	0.08	15.18	7.0	0.007	12.52	7.0	0.57
60	16.60	13.3	0.07	11.07	13.2	0.08	16.71	12.75	0.008	10.71	12.66	1.46
80	15.81	19.3	0.08	12.28	18.1	0.09	14.23	15.4	0.009	12.06	15.2	2.11
100	16.28	22.66	0.08	12.35	23.15	0.09	16.75	21.2	0.010	11.42	21.25	2.63
120	16.05	29.16	0.09	11.47	25.66	0.09	20.53	23.84	0.012	10.32	21.72	3.23
140	16.51	36.11	0.09	11.26	33.91	0.10	16.33	30.4	0.014	10.18	29.1	3.68

It should be noted that in the absence of noise during the estimation of distances, the triangular method can find the position of nodes without error. The reason is that it is an exact method that uses mathematical formulas. However, in practice, due to the presence of noise, the quality of this algorithm is greatly reduced. In Table 1, the average number of unknown nodes and the execution time of the algorithms are also shown.

As mentioned before, if the usual sensor nodes are present at points that are not within the range of receiving beacons from reference nodes, they cannot be known. The average of the least number of unknown nodes belongs to the proposed method and the triangular method. In most experiments, these two algorithms could detect more nodes than the IPSO and PSO algorithms. The reason for this is that the proposed algorithm and the triangular method use the technique of converting a usual sensor node to a secondary reference. In fact, each usual sensor node that detects its location becomes a secondary reference node. Each secondary reference node within the R range sends beacons and introduces its location. This technique helps an unknown node estimate its location, provided that the unknown node is located in the vicinity of a secondary reference node and uses the beacons received from that location. On the other hand, the IPSO and PSO algorithms do not use the technique of becoming a secondary reference. Table 1 shows that the more the number of sensor nodes in the environment (the density of the sensors in the environment increases), the less the number of undetected nodes in the proposed algorithm and the triangular method compared to the IPSO and PSO algorithms.

Although the proposed algorithm, with the presence of noise in the environment, has had the least error rate, it does not have a relatively short runtime. This is due to the heavy calculations of the COA algorithm. This is one of the disadvantages of the proposed method. In contrast, the triangular method, due to the low volume of calculations, has a very short runtime. However, the triangular method increases the error rate by increasing the amount of noise in the environment and as a result, its efficiency decreases. The average runtime of the three COA, IPSO and PSO algorithms was reported in Table 1 with the condition of terminating after 100-iterations.

The triangular method is also non-iterative because it is not an evolutionary algorithm. This method focuses on the localization of unknown nodes in three steps. In Figure 11, the status of the known and unknown nodes is represented by the COA algorithm. It can be seen from Figure 11 that the location of 20 nodes out of 100 sensor nodes is not detected. These nodes are shown with the red stars. In addition, nodes whose locations are detected by the algorithm are shown in the form of a blue star and their actual location is shown as blue dots. The distance between the estimated location and the actual location of a node determines the value of the localization error of that node. The nodes whose locations have been detected send beacons, as a secondary reference, in the range shown in yellow color. Figure 11 estimates the location of nodes with 5% noise.

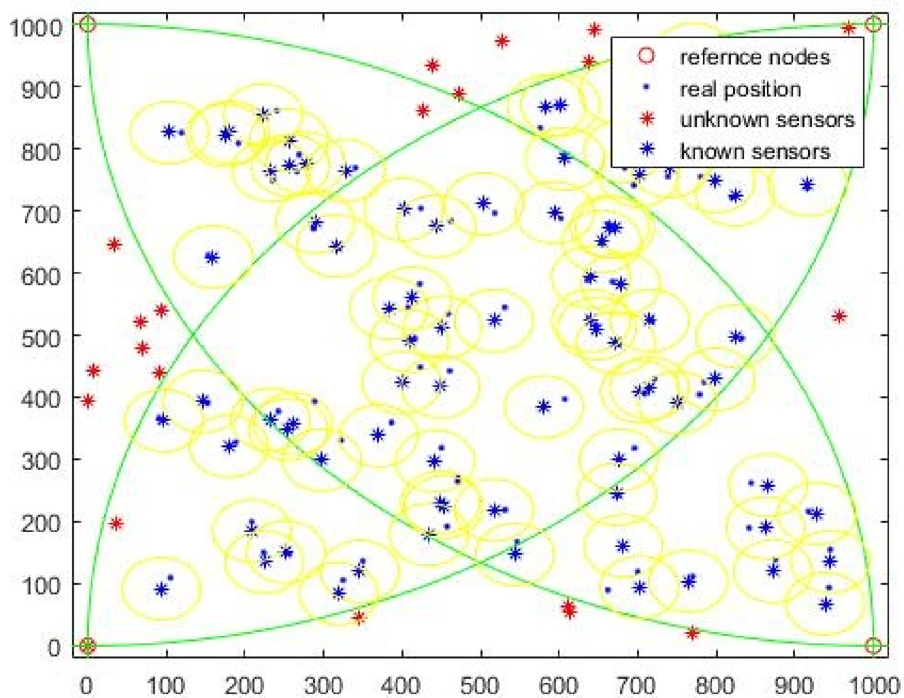

Figure 11. Displaying the known and unknown nodes in the area by the COA algorithm

In Figure 12, the average localization error of algorithms is shown with different noise levels. This experiment was performed with the presence of 80 sensor nodes. As shown in the Figure 12, the average error of all algorithms has increased with the increase in the noise level from 2% to 8%. However, the increase in the average error of the triangular method has been much higher than that of the other algorithms. This point indicates the excessive sensitivity of the triangular method to the noise level. Of the four algorithms compared, the COA algorithm has had the lowest average error of localization. In Figure 13, the number of nodes detected by each algorithm is shown. This experiment was performed with a 5% noise level and 100, 150, and 200 sensor nodes.

The proposed algorithm and the triangular method, due to the use of secondary reference nodes technique, could detect more nodes than the IPSO and PSO algorithms. This figure shows that by increasing the number (density) of nodes in the environment, the ability of the proposed algorithm to detect nodes increases, while this ratio remains almost constant for the IPSO and PSO algorithms.

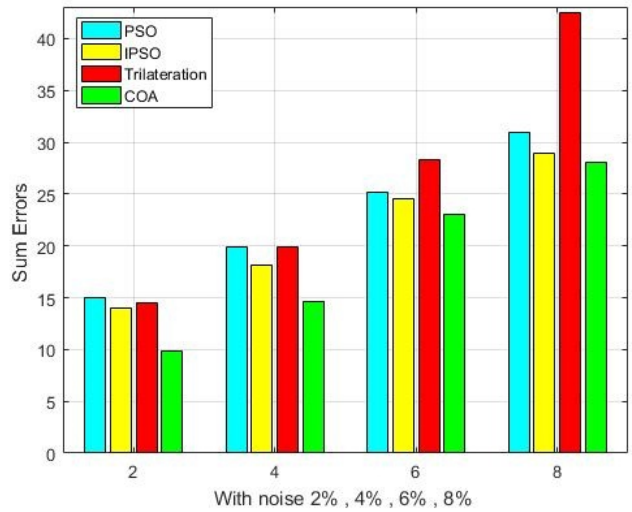

Figure 12. Average localization error of algorithms with different noise values

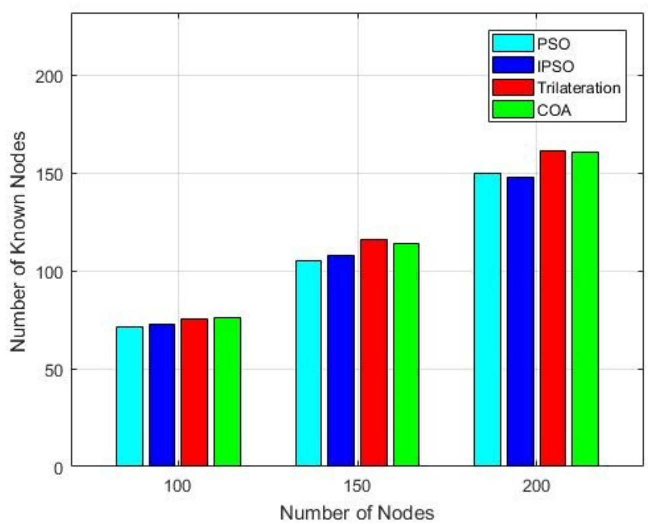

Figure 13. Number of nodes known by the algorithms

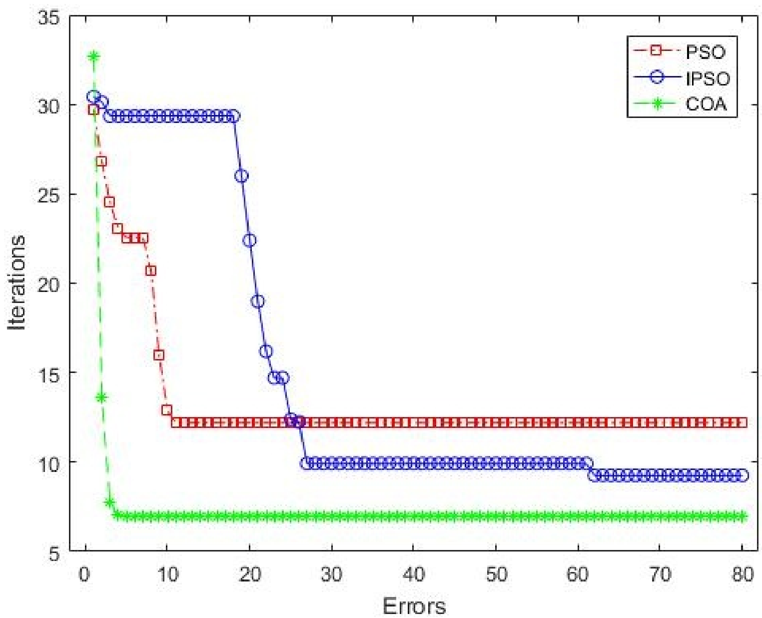

Figure 14. Convergence diagram of algorithms

Figure 14 shows the convergence diagram of three metaheuristic algorithms. This convergence diagram shows the localization of a specific sensor node by three different algorithms. The triangular method has not been considered in this experiment due to its different essence. As can be seen, the COA algorithm could converge much faster than the two IPSO and PSO algorithms. This is because of the ability of the COA algorithm to search. On the other hand, the IPSO algorithm could perform better than the PSO algorithm due to the improvement carried out to it by the authors of the article [18] and avoid the local minimum trap.

6. Conclusion

In the underwater wireless sensor networks, the process of estimating the location of a sensor node is called localization. In this paper, the proposed method was introduced based on the cuckoo optimization algorithm to solve the localization problem. In this method, first, the sensor node calculates its distance from three reference nodes by the TOA technique. If a node is located in a position where it cannot receive beacons from at least three reference nodes, it remains unknown. Otherwise, each sensor node estimates its location by running the COA algorithm. The proposed method was compared with the triangular method and IPSO and PSO algorithms in terms of the two criteria, namely the localization error and the number of detected nodes. In the case of the localization error, it was observed that the COA algorithm could perform the localization more accurately than other methods. In the case of the number of detected nodes, the proposed method has had the best performance similar to that of the triangular method and has found more nodes compared to the IPSO and PSO algorithms.

One of the disadvantages of the proposed method is its runtime. The reason for this is the complex calculations of the COA algorithm. It is possible to reduce the runtime of the proposed algorithm by reducing the number of cuckoos population and the number of algorithm iterations. This creates equilibrium between the localization error and runtime. Future research in this domain can include the use of other metaheuristic algorithms, the addition of the initial number of reference nodes, and the use of mobile references.

References

[1] Nayyar, V. Puri, and D.N. Le, “Comprehensive Analysis of Routing Protocols Surrounding Underwater Sensor Networks (UWSNs),” In Data Management, Analytics and Innovation, 2019.

[2] H. Alrezaamiri, M. Golsorkhtabaramiri, M. Farmanbar, and H. Naeemaeiaali, “A high throughput CDMA-based reader collision avoidance protocol for RFID networks (HRCP),” Journal of Advances in Computer Research, 2015.

[3] Bhattacharjya, X. Zhong, J. Wang, and X. Li, “Security Challenges and Concerns of Internet of Things (IoT),” In Cyber-Physical Systems: Architecture, Security and Application, 2019.

[4] Bagherizadeh, Mehdi, and Rezvan Kazemi. "A high performance and secure way to time synchronization in wireless sensor network." *Journal of Advances in Computer Research*, 2017.

[5] M.T. Isik and O.B. Akan, “A three dimensional localization algorithm for underwater acoustic sensor networks,” IEEE Transactions on Wireless Communications, 2009.

[6] C.H. Yu, K.H. Lee, H.P. Moon, J.W. Choi and Y.B. Seo, “Sensor localization algorithms in underwater wireless sensor networks,” In ICCAS-SICE, 2009.

[7] Yahya and J. Ben-Othman, “A scalable and energy-efficient hybrid-based MAC protocol for wireless sensor networks,” In Proceedings of the 3nd ACM workshop on Performance monitoring and measurement of heterogeneous wireless and wired networks, 2008.

[8] Mirza and C. Schurgers, “Motion-aware self-localization for underwater networks,” In Proceedings of the third ACM international workshop on Underwater Networks, 2008.

[9] Y. Zhang, S. Liu and Z. Jia, “Localization using joint distance and angle information for 3D wireless sensor networks,” IEEE communications letters, 2012.

[10] E.L. Lloyd, and G. Xue, “Relay node placement in wireless sensor networks,” IEEE Transactions on Computers, 2007.

[11] M. Erol, L.F. Vieira, A. Caruso, F. Paparella, M. Gerla and S. Oktug, “Multi stage underwater sensor localization using mobile beacons,” In Sensor Technologies and Applications, 2008.

[12] R. Zandi, M. Kamarei and H. Amiri, “Distributed estimation of sensors position in underwater wireless sensor network,” Int. J. Electron. 2016.

[13] L. Meiqin, G. Xiaodong and Z. Senlin, “Localization based on best spatial correlation distance mobility prediction for underwater wireless sensor networks,” in: 34th Chinese Control Conference, Hangzhou, 2015.

[14] Ebrahimnejad, Z. Karimnejad and H. Alrezaamiri, “Particle swarm optimisation algorithm for solving shortest path problems with mixed fuzzy arc weights,” International Journal of Applied Decision Sciences, 2015.

[15] Ebrahimnejad, M. Tavana and H. Alrezaamiri, “A novel artificial bee colony algorithm for shortest path problems with fuzzy arc weights,” Measurement. 2016.

[16] H. Alrezaamiri H, A. Ebrahimnejad and H. Motameni, “Software requirement optimization using a fuzzy artificial chemical reaction optimization algorithm,” Soft Computing. 2018.

[17] R. Rajabioun,” Cuckoo Optimization Algorithm,” Soft Computing, 2011.

[18] Z. Ying and L. Jixing, “A kind of nodes localization method for three-dimensional UWSNs,” In Control Conference (CCC), 2015 34th Chinese, 2015.

[19] Esfandiari, Ahmad. "Cuckoo optimization algorithm in cutting conditions during machining." *Journal of Advances in Computer Research* 5.2, 2014.

[20] F. Akhoundi, A. Minoofar, and J. A. Salehi, “Underwater positioning system based on cellular underwater wireless optical cdma networks,” in Wireless and Optical Communication Conference (WOCC), 2017.

[21] N. Saeed, T. Y. Al-Naffouri, and M.-S. Alouini, “Outlier detection and optimal anchor placement for 3-D underwater optical wireless sensor network localization,” IEEE Trans, 2019.