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Performance of SALP Swarm Localization Algorithm in Underwater Wireless Sensor Networks

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Abstract: In underwater wireless sensor networks, the optimization strategies for localization might be seen as a new boon for the localization of sensor nodes (UWSNs). The techniques for optimization are those that repair the incorrect value, adapt it to the situation, and correct it. Because the algorithm could adapt to the constantly changing environment, it was widely used in terrestrial applications, and the same can be extended to the underwater environment with modifications. To address the localization issue that arises in UWSNs, the Underwater Salp Swarm Algorithm (USSA), a nature-inspired node localization algorithm, has been presented. With the help of this technique, an effort to discover a solution to the localization problem as an optimization problem is considered. The proposed algorithm is accessed in a simulated water environment. The energy is assigned to the anchor well as non-localized nodes, after deploying them in the simulated underwater network. The suggested algorithm is compared with other optimization algorithms, such as UPSO and UBOA, with reference to the computing time, localization accuracy, and the number of localized nodes. It is possible to localize a greater number of nodes in a much faster and more efficient way by considering the proposed algorithm.

Keywords: localization; non-localized nodes; UWSNs; USSA

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1. Introduction

The natural meta-heuristic algorithm's ability to provide better accuracy in real-world applications makes it a good substitute for numerous ancient node localization algorithms. Apart from this, it also showcases properties such as local optima avoidance, gradient-free mechanisms, and flexibility. The meta-heuristics take up the optimization issue as a black box, which effectively eliminates the calculation of search space derivatives, which, in turn, makes the algorithm largely flexible for resolving a different range of problems. Moreover, they also benefit from random operators, as they represent the family of stochastic optimization techniques. This helps them to evade local solutions during the occasion of resolving the actual issues, which generally have huge amounts of local optima.

Generally, there are two types of meta-heuristic techniques: evolutionary and swarm intelligence techniques. Evolutionary techniques are the notion of nature's evolution. The most popular example is a Genetic Algorithm (GA). Swarm intelligence techniques, on the other hand, imitate the intelligence of swarms or flocks of living beings in nature. The basis of these algorithms is the collective behavior of a cluster of creatures. This helps them to provide the improvement in a set of solutions, which, in turn, makes them popular over the evolutionary algorithms. Some of these natural meta-heuristic algorithms involve the Grey Wolf Optimizer (GWO) Algorithm, the Particle Swarm Optimization (PSO) Algorithm, the Firefly Algorithm (FA), the Butterfly Optimization Algorithm (BOA), and the Salp Swarm Algorithm (SSA). Numerous studies, such as Gopkumar and Jacob [1], Harikrishnan et al. [2], Fouad et al. [3], etc., were conducted on the application of various swarm algorithms on the terrestrial surface. However, the applicability of these algorithms in underwater communication is not yet widely explored. Hence, the present chapter analyzes the performance efficiency of the Salp optimization algorithm in the localization of non-localized nodes in UWSNs. This study attempts a comparative analysis of the performance of Salp and two other naturally inspired algorithms, such as BOA and PSO algorithms, in the underwater environment. The subsequent subsections will provide the functional theory of all three algorithms.

2. Background

2.1. Butterfly Optimization Algorithm

The Butterfly Optimization Algorithm (BOA) is a nature-stimulated swarm intelligence algorithm suggested by [4]. The functioning of the algorithm took its inspiration from the food-searching mannerisms of butterflies.

These butterflies function as the search agents that perform optimization. It is presumed that each butterfly produces a fragrance with a certain intensity. This fragrance is spread across and detected by various butterflies in the area. The radiated fragrance is directly associated with the butterfly's fitness, i.e., the fragrance radiated by a butterfly changes in accordance with its current location [4]. If a butterfly senses a larger quantity of fragrance from another butterfly within the region, it moves towards that other butterfly, which is referred to as a global search. On the other hand, if a butterfly cannot experience a larger fragrance than its own, it moves randomly, which is referred to as a local search [5].

The fragrance is defined as "the function of a stimulus physical intensity" and it is formulated as

$$f_i = C\, I^{\,a} \tag{1}$$

where

f_i is the apparent scale of fragrance;
C is the modality of sensing;
I is the intensity of stimuli;
a is the exponential power relays on modality, accounting for the changing degree of absorption.

As discussed above, the BOA algorithm has two phases, namely, the global and the local search phases. The global search phase witnesses the movement of the butterfly towards the best butterfly/solution g* . This can be denoted using the formula

$$x_i^{\,t+1} = x\,_i^t + \left(r^2 \times g^* \; - x\,_i^t\right) \times f_i \tag{2}$$

where

$x\,_i^t$ is the solution vector x_i of the ith butterfly in the ith iteration;
g^* is the best solution achieved in the present stage;
f_i is the ith butterfly's fragrance;
r is a random number in [0, 1].

Further, the local search phase can be calculated as

$$x_i^{\,t+1} \;=\; x_i^t + \left(r^2 \times x\,_k^t - x\,_j^t\right) \times f_i \tag{3}$$

where

x_i^t and x_k^t = jth and kth butterflies selected randomly from the solution space.

Equation (3) will represent a local random walk if r represents a random number in [0, 1] and x_i^t and x_k^t belongs to the same subswarm.

As the butterflies search on a global and local scale for food and mating partners, the algorithm also involves a switch probability to shift between the intensive local and the common global searches.

2.2. Particle Swarm Optimization Algorithm

Particle swarm optimization (PSO) is another optimization algorithm inspired by the movements of creatures in nature. The algorithm was suggested by [6]. The execution of this algorithm is based on the swarm activities of fish schooling and bird flocking. This algorithm employs the movement of a swarm population, simulated by several particles around the search area to discover the finest solution. Every individual particle yields a resolution to the problem, which is generally characterized as a point in the D-dimensional space. Each particle's position is denoted as, $x_i = (x_{i1}, x_{i2}, \ldots x_{iD})$. The velocity with which every particle moves in the search space to find the optimal solution is presented as, $v_i = [v_{i1}, v_{i2}, \ldots v_{iD}]$. During this motion, every single particle's position is updated with reference to the best position attained by the particle itself, and the best position achieved by all of the particles so far. The best position attained by the particle itself is known as p_{best}, and the best position achieved by all of the particles is referred to as g_{best}. The best result for every particle stored in p_{best} and the best result for the entire population stored in g_{best} is used for comparison during the upcoming iteration.

The updated position and velocity of each particle can be formulated as

$$x_{id}{}^{t+1} = x\,{}^{t}_{i\,d} + v\,{}^{t+1}_{i\,d} \tag{4}$$

$$V_{id}{}^{t+1} = w * \; v^{t}_{i\,d} + c_1 \; * r_1 * \left(p_{i\,d} - x^{t}_{i\,d}\right) + c_2 * r_2 * \left(p_{g\,d} - x^{t}_{i\,d}\right) \tag{5}$$

where

t is the iteration number;
w is the weight due to inertia;
c_1 and c_2 are the constants of acceleration;
r_1 and r_2 are the random variables whose values are distributed within [0, 1];
$p_{i\,d}$ and $p_{g\,d}$ are the p_{best} and g_{best} rudiments in the dth dimension.

The velocity is restricted by a predefined peak value v_{max}.

2.3. SALP Optimization Algorithm

Salps belong to the Salpidae family, with the body structure of a limpid cylinder. They resemble jellyfish in their movement and texture. The Salp's shape is depicted in Figure 1a. These creatures follow a special swarm movement. They move forward as a result of the push of the water [7]. This swarming attitude is the chief inspiration for the development of an algorithm called the Salp Swarm Algorithm [8]. These Salps form a Salp chain in the oceans, which helps these creatures to attain the best movements in the foraging process. This chain is demonstrated in Figure 1b.

Mathematical Model

In order to create a mathematical model for the Salp chains, the entire Salp population in a chain is divided into two groups, namely, the head and the followers. The head is the start of the chain, and the remainders of the chain are the followers [9].

The Salp's position is defined in a search space of dimension n, where n signifies the number of variables in the problem.

Then, a 2D matrix with the name x, which reserves the position of each Salp, is defined. There is also an assumed food source as the target of the swarm. The position of a leader is upgraded using the equation

$$x_I{}^j \begin{cases} f_j \; + c_1\left(\left(ub_{\,j} - Ib_{\,j}\right)c_2 + Ib_{\,j}\right), c_3 \geq 0 \\ f_j - c_1\left(\left(ub_{\,j} - Ib_{\,j}\right)c_2 + Ib_{\,j}\right), c_3 < 0 \end{cases} \tag{6}$$

where

$x_I{}^j$ is the leader Salp's position in the jth dimension;
f_j is the food source's position in the jth dimension;
$ub_{\,j}$ is the jth dimension's upper bound;
$Ib_{\,j}$ is the jth dimension's lower bound;
c_1, c_2, and c_3 are random numbers.

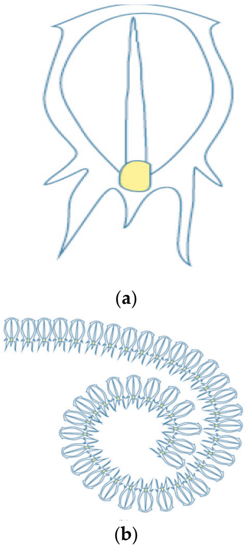

(**a**)
(**b**)

Figure 1. (**a**) Individual Salp, (**b**) Salp chains.

From Equation (6), it is clear that the updating of the leader's position solely depends on the food source.

The coefficient c_1 is a vital parameter in USSA, as it strikes the balance of exploration and exploitation. Hence, it is calculated as

$$C_1 = 2e^{-\left(4\,{}^{l}/_{L}\right)^2} \tag{7}$$

where

l is the present iteration;
L is the peak count of iterations.

The parameters c_2 and c_3 represent random numbers regularly produced in the interval of [0, 1]. The importance of these parameters is that they determine whether the next position of the leader in the jth dimension should be towards positive or negative infinity. Apart from that, they also determine the step size.

Meanwhile, the updating of the follower's position is performed using the equation of Newton's law of motion, which is formulated as

$$x_i^j = \frac{1}{2}a\,t^2 + v_0 \tag{8}$$

where

$i \geq 2$;

x_i^j is the ith follower Salp's position in the jth dimension;
t is the time;
v_0 is the initial speed;
a is v_{final}/v_0;
and $v = x - x_0/t$.

Because iteration is the time in optimization, the difference between iterations is 0 and 1, and if $v_0 = 0$, then the equation can be modified as

$$x_i^j = \frac{1}{2}\left(x_{\ i}^{\ j} + x_{\ j}^{\ i-1}\right) \tag{9}$$

where

$i \geq 2$;
x_i^j is the ith follower Salp's position in the jth dimension.

The Salp chains can be simulated using Equations (6) and (9).

The following section will provide a description of the localization of non-localized nodes in UWSN using the Salp's algorithm.

3. Node Localization Using Underwater Salp Swarm Optimization Algorithm (USSA)

Despite proposing Salp to solve the localization problem, the study understood that these mathematical models cannot be directly used to find the solution to optimization problems in the underwater environment. Hence, the study modified the algorithm to chase the moving global optimum [10], which in turn facilitates the localization of all non-localized nodes. The localization procedure is detailed in the subsequent paragraphs.

The USSA approached the global optimum by introducing several Salps with random positions [11]. Then, it estimated the fitness of every Salp to figure out the Salp with the best fitness. Once this had been determined, the algorithm assigned the best Salp's position as the source food, represented by variable F, to be searched by the rest of the Salp chain. In the meantime, the coefficient c_1, which balances the exploration process, was updated using Equation (9). The entire process was iteratively executed until all non-localized nodes were localized.

Key Features of USSA

There are certain key advantages of the USSA, which make the algorithm capable of localizing the nodes. These features are specified below:

- In each iteration, the USSA preserves the best solution achieved thus far and allocates it to the global optimum variable [12]. This process helps to prevent the loss of the solution, even in the case of the deterioration of whole populations.
- The USSA updates the leading Salp's position only with reference to the best solution attained so far. This ensures that the leader continuously explores the space around it, which in turn enables the localization [13] of other non-localized nodes.
- The position of the follower Salps, with reference to one another, has been updated by the algorithm. This helps the followers to gradually approach the leading Salp.
- Further, this gradual movement of follower Salps prevents the stagnation [14] of the algorithm.
- The adaptive decreasing of parameter c_1, along with the iterations [15], enables the algorithm to explore the search space first before exploiting it.
- There is only a single major controlling parameter (c_1) for the USSA.

4. Performance Comparison and Results

4.1. Simulation Setups and Determination of Performance Parameters

This study conducts a performance comparison of the Underwater SALP Swarm Optimization Algorithm (USSA) with the Underwater Particle Swarm Optimization Algorithm

(UPSO), and the Underwater Butterfly Optimization Algorithm (UBOA). The performance parameters, such as the computing time, the number of localized nodes, and the localization error are measured as a part of analyzing the performance of the selected algorithms. MATLAB was used to perform the simulation.

Simulation Settings

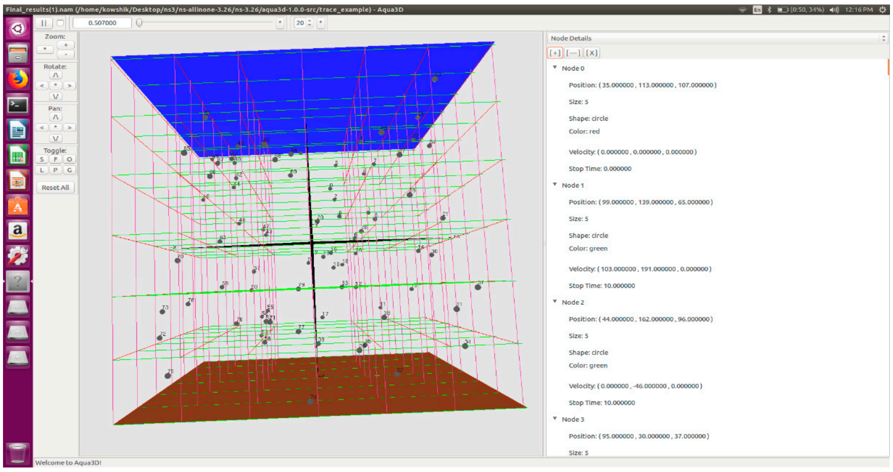
The simulation parameters used for the proposed optimization algorithm are depicted in Table 1.

Table 1. Simulation settings.

Parameter Description	Value
Total Number of Nodes	50, 100, 150
Area of the Sensing Field	1000 m × 1000 m × 1000 m
Number of Anchor Nodes	10, 20, 30
Simulation Time	10 s
Channelling Mode	AODV

The anchor nodes are the nodes that already know their location and have the highest energy in the underwater environment.

The result addresses the problems during the localization of non-localized nodes in the 3-D underwater environment. The study found out that the determination of the sensor node's 3-D position coordinates in the real-time aquatic environment is one of the major challenges faced during the localization of nodes, and that a proper visualization tool can help to overcome this difficulty. A sample deployment representation is shown in Figure 2.



Final_results(1).nam (/home/kowshik/Desktop/ns3/ns-allinone-3.26/ns-3.26/aqua3d-1.0.0-src/trace_example) - Aqua3D

0.507000 20

Node Details

- Node 0
  - Position: (35.000000 , 113.000000 , 107.000000)
  - Size: 5
  - Shape: circle
  - Color: red
  - Velocity: (0.000000 , 0.000000 , 0.000000)
  - Stop Time: 0.000000
- Node 1
  - Position: (99.000000 , 139.000000 , 65.000000)
  - Size: 5
  - Shape: circle
  - Color: green
  - Velocity: (103.000000 , 191.000000 , 0.000000)
  - Stop Time: 10.000000
- Node 2
  - Position: (44.000000 , 162.000000 , 96.000000)
  - Size: 5
  - Shape: circle
  - Color: green
  - Velocity: (0.000000 , -46.000000 , 0.000000)
  - Stop Time: 10.000000
- Node 3
  - Position: (95.000000 , 30.000000 , 37.000000)
  - Size: 5

Welcome to Aqua3D!

Figure 2. Sensor Node Deployment.

The coordinate values change during the simulation time. The node 1 coordinate values can be observed in Figure 3.

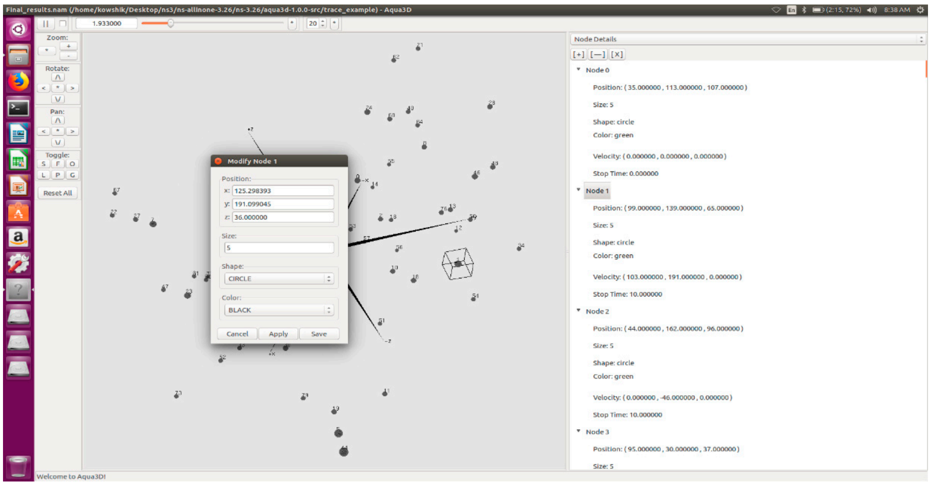
A sample view of node 49, changing with respect to the simulation time, can be observed in Figure 4. The total simulation time considered is 10 s, and the observation and comparative analysis of the work are carried out for 2 s.

The findings of the comparative analysis are provided in the subsequent section.

4.2. Results

4.2.1. Computing Time

Figure 5 depicts the findings of the comparative analysis of the proposed USSA, UBOA, and UPSO, with respect to the computing time.



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1.933000 20

Modify Node 1

Position:
x: 125.298393
y: 191.099045
z: 36.000000

Size: 5

Shape: CIRCLE

Color: BLACK

Node Details

Node 0
Position: (35.000000 , 113.000000 , 107.000000)
Size: 5
Shape: circle
Color: green
Velocity: (0.000000 , 0.000000 , 0.000000)
Stop Time: 0.000000

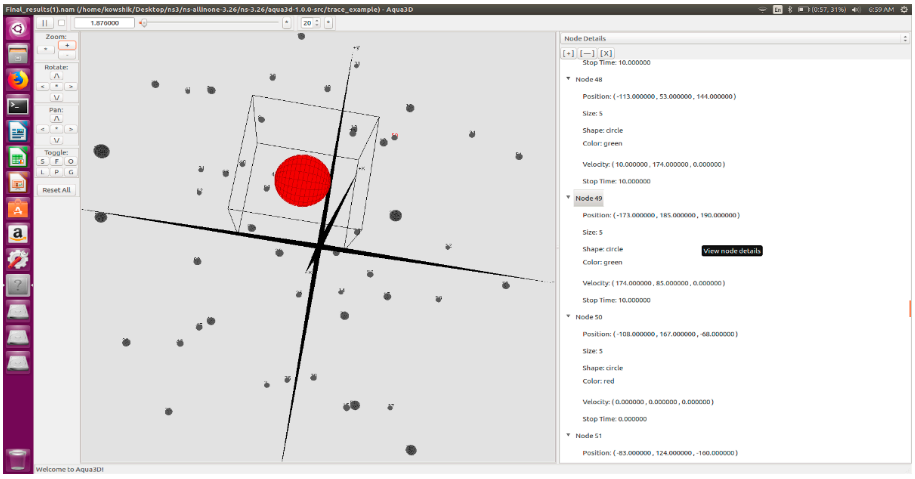
Node 1
Position: (99.000000 , 139.000000 , 65.000000)
Size: 5
Shape: circle
Color: green
Velocity: (103.000000 , 191.000000 , 0.000000)
Stop Time: 10.000000

Node 2
Position: (44.000000 , 162.000000 , 96.000000)
Size: 5
Shape: circle
Color: green
Velocity: (0.000000 , -46.000000 , 0.000000)
Stop Time: 10.000000

Node 3
Position: (95.000000 , 30.000000 , 37.000000)
Size: 5

Welcome to Aqua3D!

Figure 3. Node Coordinate values.



Final_results(1).nam (/home/kowshik/Desktop/ns3/ns-allinone-3.26/ns-3.26/aqua3d-1.0.0-src/trace_example) - Aqua3D

1.876000 20

Node Details

Stop Time: 10.000000

Node 48
Position: (-113.000000 , 53.000000 , 144.000000)
Size: 5
Shape: circle
Color: green
Velocity: (10.000000 , 174.000000 , 0.000000)
Stop Time: 10.000000

Node 49
Position: (-173.000000 , 185.000000 , 190.000000)
Size: 5
Shape: circle
Color: green
Velocity: (174.000000 , 85.000000 , 0.000000)
Stop Time: 10.000000

Node 50
Position: (-108.000000 , 167.000000 , -68.000000)
Size: 5
Shape: circle
Color: red
Velocity: (0.000000 , 0.000000 , 0.000000)
Stop Time: 0.000000

Node 51
Position: (-83.000000 , 124.000000 , -160.000000)

Welcome to Aqua3D!

Figure 4. Node location values being updated during simulation.

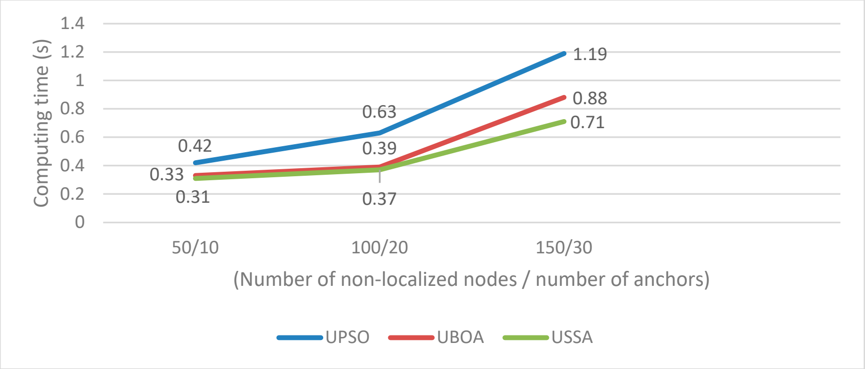


Figure 5. The computing time of the various localization algorithms in multiple UWSN deployments.

It can be inferred from Figure 5 that the computation time of all the algorithms kept increasing, with reference to the rise in the number of the non-localized nodes and the anchor nodes. However, Figure 5 makes it clear that the proposed USSA took lesser computing time in comparison with the other two algorithms. This was evident for all the selected non-localized nodes–number of anchor combinations [16]. Even though the UBOA showcased an almost similar performance in a lesser number of the non-localized nodes and the anchor nodes combination, the gap kept widening as the count of the non-localized nodes and the anchor nodes increased; in the end, it took a computing time of 0.88 s to localize 150 non-localized nodes with the help of 30 anchor nodes, whereas the USSA only took 0.71 s. The comparison of the USSA with the UPSO demonstrated a much wider gap in the computing time, with the UPSO having a much higher computing time compared with the USSA. Hence, the result proves the performance supremacy [17] of the USSA over the UBOA and the UPSO in the localization of non-localized nodes, with reference to the computing time.

4.2.2. Number of Localized Nodes

Figure 6 depicts the findings of the comparative analysis of the proposed USSA, UBOA, and UPSO, with reference to the number of localized nodes.

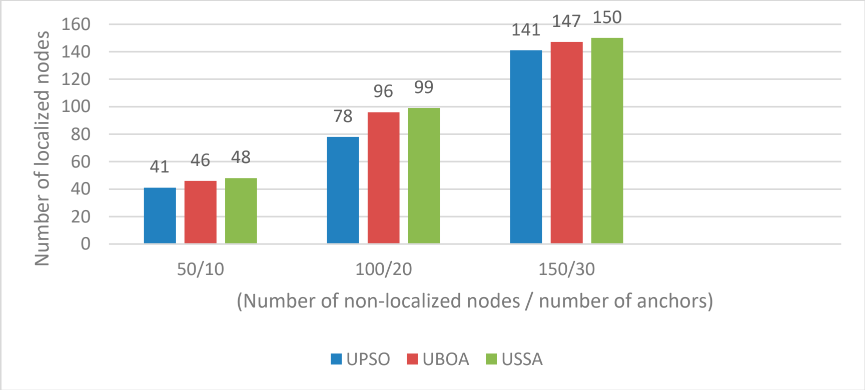


Figure 6. The number of localized nodes of the various localization algorithms in multiple UWSN deployments.

Figure 6 makes it clear that the proposed USSA managed to localize the highest number of non-localized nodes in comparison with the contemporary algorithms. This performance supremacy was evident in different non-localized anchor nodes combinations, even though the UBOA performed very closely. Further, the rise in the number of localized nodes, with reference to the rise in the non-localized node and anchor node density [18], indicates that the count of localized nodes increases along with the surge in the count of anchor nodes. This also proves the performance efficiency of the proposed USSA.

4.2.3. Localization Error

The findings of the comparative analysis of the USSA, UBOA, and UPSO, with respect to the localization error, are depicted in Figure 7.

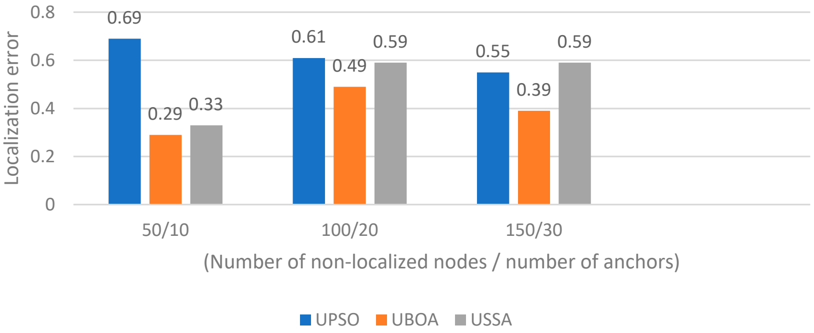


Figure 7. The localization error of the various localization algorithms in multiple UWSN deployments.

The findings, as indicated in Figure 7, revealed that the UBOA yielded the best output with the least localization error among the three algorithms. The proposed USSA yielded a result close to the best performer UBOA when the count of the anchor and non-localized nodes was less (yielded an output with a localization error of 0.33 for 50 non-localized nodes and 10 anchor nodes). However, the error rate of the proposed USSA increased as the count of the anchor nodes and non-localized nodes increased. Despite this increase, it maintained a constant error value with reference to the upsurge in the number of non-localized nodes and anchor nodes. This result justifies the selection of the USSA to a certain extent, as with these constant error rates, it is possible to localize more number of nodes by increasing the number of anchor nodes [19]. In addition, the superior performance of the USSA over the UPSO also indicates that the proposed USSA is not an incorrect choice.

4.3. Performance Metrics of Selected Localization Algorithms

The summary of the performance analysis of the selected localization algorithms is described in the subsequent Tables 2 and 3.

Table 2. Performance metrics of various localization algorithms.

Non-Localized Nodes	Anchor Nodes	No. of Iterations	UPSO			UBOA			USSA		
			E_l (m)	T (s)	N_l	E_l (m)	T (s)	N_l	E_l (m)	T (s)	N_l
50	10	10	0.81	0.41	40	0.22	0.33	45	0.32	0.31	48
		20	0.79	0.42	41	0.26	0.32	45	0.36	0.29	48
		30	0.69	0.42	41	0.29	0.33	46	0.33	0.31	48
100	20	10	0.77	0.62	77	0.44	0.43	96	0.54	0.41	98
		20	0.71	0.63	79	0.45	0.42	96	0.55	0.40	97
		30	0.61	0.63	78	0.49	0.39	96	0.59	0.37	99
150	30	10	0.60	0.99	137	0.33	0.77	146	0.43	0.66	148
		20	0.60	1.11	135	0.35	0.78	146	0.45	0.68	148
		30	0.55	1.19	141	0.39	0.88	147	0.59	0.71	150

Table 3. Summary of experimental results of the various localization algorithms.

Non-Localized Nodes	Anchor Nodes	UPSO			UBOA			USSA		
		E_l (m)	T (s)	N_l	E_l (m)	T (s)	N_l	E_l (m)	T (s)	N_l
50	10	0.69	0.42	41	0.29	0.33	46	0.33	0.31	48
100	20	0.61	0.63	78	0.49	0.39	96	0.59	0.37	99
150	30	0.55	1.19	141	0.39	0.88	147	0.59	0.71	150

Table 2 demonstrated that the rise in the number of iterations causes a corresponding rise in computing time. This was evident with respect to all selected algorithms. The reason is that, as the number of iterations rises, a larger amount of computations is required, which, in turn, leads to a longer computation time. Meanwhile, the localization error, as well as the number of localized nodes, showcased a mixed result with no clear pattern to indicate the relationship of these performance metrics with the number of non-localized nodes, as well as anchor nodes. Further, Tables 2 and 3 also indicated the supreme performance of the suggested USSA with reference to the number of localized nodes and the computing time. This performance supremacy was evident across different iterations and various combinations of non-localized and anchor nodes. In brief, Tables 2 and 3 justify the proposal of the USSA and the iterative procedure.

5. Conclusions

In this paper, a nature-inspired node localization algorithm named the Salp Swarm Algorithm (USSA) has been proposed to tackle the localization problem occurring in the UWSNs. This algorithm handled the localization problem as an optimization problem and attempted to find a solution. The suggested USSA has been implemented in a simulated environment and was validated using various numbers of non-localized and anchor nodes. Furthermore, the suggested algorithm was assessed and compared with other existing optimization algorithms, namely the UPSO and the UBOA, with reference to computing time, localization accuracy, and the number of localized nodes. The simulation results substantiated the performance supremacy of the proposed USSA over the other two localization algorithms with respect to the number of localized nodes and the computing time. Even though the UBOA yielded the best output with the least localization error, the close result yielded by the proposed USSA when the number of anchors and non-localized nodes is less indicated that the USSA was not a bleak performer. Moreover, the constant error value it maintained also justifies the selection of the USSA to a certain extent, as with these constant error rates, it is possible to localize more nodes by raising the number of anchor nodes. In brief, the proposal of the USSA is justified by its performance efficiency.

6. Discussion

A naturally inspired Underwater Salp Swarm Algorithm (USSA) was proposed and the performance was compared with other existing optimization algorithms, namely the UPSO and UBOA, with respect to the computing time, the localization accuracy, and the number of localized nodes. The findings substantiated the performance supremacy of the proposed USSA over the other two localization algorithms [20], with respect to the parameters, the number of localized nodes, and the computing time. The findings demonstrated that the suggested USSA only took 0.71 s to localize 150 nodes, whereas the UBOA took 0.88 s and the UPSO took 1.19 s. Even though the UBOA yielded the best output with the least localization error among the selected algorithms, the close result yielded by the proposed USSA when the number of non-localized and anchor nodes was lower [21] (yielding an output with a localization error of 0.33, where the UBOA demonstrated an error rate of 0.29, for 50 non-localized nodes and 10 anchor nodes), indicated that the USSA was not a bleak performer. Moreover, the constant error value it maintained also justifies the selection of the USSA to a certain extent, as with these constant error rates, it is possible to localize a greater number of nodes [22] by raising the number of anchor nodes.

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