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A Novel 3D Indoor Node Localization Technique Using Weighted Least Square Estimation with Oppositional Beetle Swarm Optimization Algorithm

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Abstract: In this research work an effective indoor localization mechanism has been implemented for smart devices, advancements of mobile-Internet and multimedia applications. Indoor localization is one of recent technology, it is a location-based service (LBS), this work has been facilitated to commercial and civilian industries. The LSB can useful in many tools such as public security, disaster management, and positioning navigation. Several research works have been concentrated on design of accurate 2D indoor localization techniques. Since 3D indoor localization techniques offer numerous benefits compared to 2D model. In this investigation a Novel 3D Indoor Node Localization Technique has been proposed using Oppositional Beetle Swarm Optimization with Weighted Least Square Estimation (OBSO-WLSE) algorithm. The proposed OBSO-WLSE algorithm aims to develop the localization accuracy with reduced computational time. The OBSO algorithm is employed for approximating initial locations of the targets, these results can minimize NLOS error. The precise location of target has been identified through WLSE technique as well as OBSO can predict initial location. To improve the efficiency of the OBSO technique, the concept of oppositional based learning (OBL) is integrated into the traditional BSO algorithm. The designed model prototype simulation has been run on MATLAB software with NS3 Tool Box. The measures like accuracy 98.45%, sensitivity 96.34%, recall 94.67%, 3D indoor localization detection rate 19.25% improvement and throughput 97.34% have been attained. The localization error, range error and transmission range performance measures are used for experimental evolution. The results recommended that proposed model is robust for navigation associated apps.

Keywords: 3D indoor node localization, metaheuristic algorithm, location based services, oppositional based learning, localization error

1. Introduction

The upcoming evolution in smart environments grows faster in industrial, utility, construction, shipping, home appliances, and automatic transportation. Critical techniques and investigations of smart environment are dependent upon location aware methods. They have enhanced the quality of lives and offer persons with comfort for outing, shopping, dining, working, etc. Recently, with open source android operating system and the continual decrease in hardware cost, smartphones are becoming very popular. Android or IOS dependent smartphones exist worldwide and simply obtain the location of the friends by location aware methods, such as global position system (GPS). The GPS is

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a more conventional method for outdoor localization area, and accuracy is approximately 10m error. It offered better client services in outdoor scenario. In order towards utilize the GPS in indoor atmospheres such as offices or homes, it hardly acquires the satellite signal and poor accuracy is attained. The reason is due to the complicated obstacles in building where the satellite could not communicate through the floors and walls. Therefore, an indoor localization method is needed.

Indoor localization is the procedure of attaining a client or gadget's location in either indoor atmosphere or setting. It has been widely researched in the recent ten years, mostly in Wireless Sensor Network (WSN), robotics, and industrial settings [1]. But the wide scale development of smart phones and wearable gadgets that appeared in recent years with wireless transmission abilities have found the localization and tracking of those gadgets equivalent to the tracking and localization of respective clients and allowed a wider range of relevant services and applications. The client and devices localization have a wide scale of application in industry, disaster management, health sector [2], surveillance, building management, and so on. It is also more beneficial in several new methods like smart architectures (like smart building, smart grid, smart city, Internet of Things (IoT)), and Machine Type Communication (MTC).

Since individual needs for convenient life and security increase, the requirement and range of applications for indoor localization service (ILS) also rise dramatically. The ILS is employed in various fields, like underground personnel positioning, virtual reality in cinema industry, navigation in industrial productivity workshops, and healthcare monitoring [3]. This application set contains a similar characteristic: the GPS recipient is utilized in the nearby surface or indoor atmosphere, basement that causes the attenuation of GPS signal and GPS based localization method get failed. Therefore, there is a higher requirement for the application of localization in the above-mentioned setting. Because of several characteristics, like low energy utilization, high scalable, fast deployment, comparatively inexpensive, dense node allocation, able to maintain standard efficiency in harsh atmosphere, partial dependency of framework, etc., the study and application of ILS are distinguished between conventional position obtaining manner [4]. The position data is also significant towards the application of WSN to monitor.

The node localization is a precondition to a frequent challenge for all WSNs then also it be essential for various applications of WSN such as target tracking, surveillance, etc. Basically, it plays a major part in the practicality of WSN. Here, amongst a number of localization studies that existed in the literature, several investigations are under two-dimensional localization method, while researches on three-dimensional localization are often lesser, however, it is getting more popular [5]. It is common for sensor nodes to be employed in 3D space, rather than on a horizontal position, in practical uses since objects in the interior and movement people might absorb, reflect, or block signals. The most conventional two-dimensional localization approaches be invalid for three-dimensional deployment. Therefore, new localization technique can be developed to define the position of nodes for 3D deployment in indoor setting. There are greater advantages in terms of practical relevance and application values for 3D deployment compared to 2D deployment [6].

This paper presents a Novel 3D Indoor Node Localization Technique using Oppositional Beetle Swarm Optimization with Weighted Least Square Estimation (OBSO-WLSE) algorithm. The OBSO-WLSE algorithm operates on two major phases namely determining the initial location of the targets using OBSO algorithm and determining the final location of the targets using WLSE technique. Firstly, the OBSO algorithm is employed for estimating the initial locations of the target that results in the elimination of NLOS error. The WLSE approach iteratively computes the target's ultimate position based on the beginning location provided by the OBSO technique. The performance of the OBSO technique can be improved by the integration of oppositional based learning (OBL) to the traditional BSO algorithm. Simulated results were reviewed using a variety of metrics to verify the suggested model's ability to function.

2. Literature Survey

The presented [7] rotational anchor-based localization method by utilizing Time of arrival (TOA) measurement to attain the comparative positional relation among 2 locating systems that might assist a protector to define the direction of the trapped individual in an effective way. The proposed [8] a new technique for TOA localization by 2 recipients that can be made by utilizing the reflection from a group of recognized flat reflectors [9] A new high-resolution TOA calculating approach for the IEEE 802.11 g/n range calculating inside has been shown. A 3D localization approach in light of the Chan system was suggested by [10]. The nonlinear position formula into linear method utilizing initial calculation based on 2 phase weighing least square, later it determines the location. The experimental outcomes display that the technique is easy and accurate. The TOA based technique has greater localization accuracy with least computation complexity and cheaper hardware. In addition, it is easy to design in real world which makes it familiar [11]. In the general localization technique depending upon TOA method, few proliferation paths among the base station (BS) then user terminal (UT) might be a non-line of sight (NLOS) path because of proliferation environment that has been denoted that the NLOS error might reduce the calculation efficiency & linearly raise the mean localization error [12].

To conquer these limitations, in [13, 14], few NLOS mitigating methods are presented to resolve the challenges of location calculation in the NLOS environments, therefore the NLOS BS can be determined initially & LOS BS remains utilize to calculate unknown positions of UT. By the above-mentioned NLOS mitigating methods [15], NLOS may be avoided to some extent using an upgraded Chan-Taylor 3D localization algorithm that relies on a least squares method. But it does not offer the desired accuracy in the existence NLOS technique. For overcoming this shortcoming, Chen [16] proposed a residual weighting technique (RWGH) that positions the sources by utilizing the sources through entire probable sensor set individually. Later, the residual of station is estimated depending upon the calculated source location using all set. By this residual, a weighting matrix is generated that is utilize in Taylor series calculator to attain optimum outcome with NLOS measurement.

In [17], it is demonstrated that RWGH has better efficiency by handling small scale localization methods. But, by maximum BS count, the computation complexity is high and accuracy of NLOS mitigation is decreased. It has few additional techniques, for instance, it utilizes more data to range measurement for recognizing the NLOS error. In [18] presented a method to calculate location depending upon a digital mapping of urban environmental & GPS recipient can detect the relevant satellite which may contain NLOS error. In spite of the accuracy of these techniques, it is impractical because of the absence of extra data for every environment [19]. Moreover, the above-mentioned techniques have high computational costs, difficult and unfeasible [20].

3. The Proposed Method

The working principle involved in the presented OBSO-WLSE based 3D indoor localization method is depicting in Fig. 1. The figure states that the nodes in the networks be deployed in the indoor environment. Then, the network initialization process gets executed. Once the nodes are initialized, the OBSO-WLSE algorithm is performed towards determine the actual indoor placement of the nodes. The OBSO-WLSE algorithm operates on two major phases namely determining the initial location of the targets using OBSO algorithm and determining the final location of the targets using WLSE technique.

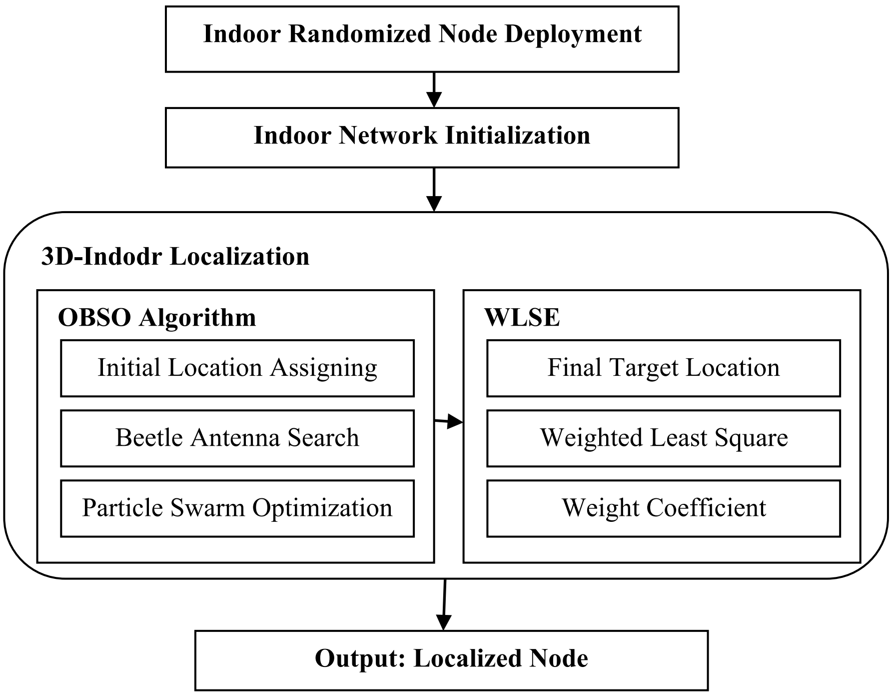

Fig. 1 - Working process of OBSO-WLSE model

The aim of this research work is to design an 3D localization technique for real time applications, usually received signal strength indication, difference of arrival and time of arrival parameters are very week to predict by 2D localization so that navigation has been critical at no signal or week signal zones. There for proposing 3D localization technique for future navigation applications. Table 1 explains about abbreviation of proposed study.

Table 1 - Abbreviation

S N O	Abbreviation	Full form
1	WLSE	Weighted Least Square Estimation
2	M-BOA	modified butterfly optimization algorithm
3	GWO	Gray wolf optimization
4	ACO	Ant colony optimization

5	PSO	Particle swarm optimization
6	OBSO	Optimized beetle swarm optimization

3.1 Problem Synthesis

Consider a localization scenario which is in a 3-D space. Let the position of the BS is represented as $s_i = [x_i, y_i, z_i]^T$, $I = 1,2,3,\cdots,n$. The original coordinates of the unknown user terminals (UT) can be defined as $u = [x, y, z]^T$. Here, the aim is to localize the UT by the use of a collection of N commonly distributed BS. During the transmission from UT to BS, the r_i remains the original distance range among the individual UT then the ith BS, that is defined by equation 1.

$$R_I = \|S_I - U\| = \sqrt{(X_I - X)^2 + (Y_I - Y)^2 + (Z_I - Z)^2} \qquad (1)$$

But owing towards the existence of NLOS, the estimated distance range amongst the UT then the ith BS is defined in Eq. (2):

$$\bar{r}_i = r_i + n_i + w_i, \qquad I = 1,2,\dots,n \qquad (2)$$

This indicates that the measurements noisew_i, has a Gaussian distribution by zero signifying that it is $w_i \sim (0,\ \sigma^2)$the NLOS error, n i, is a continuous & non-negative variable

With the criteria of LOS, the n_i worth becomes zero then the estimated distance range remains the total of original distance range & measurements noise, i.e., $\bar{r}_i = r_i + w_i$ and the measured variance is approximatelyσ, $\bar{r}_i \approx r_i$; By the existence of NLOS, n_i has non zero value too leading position. The estimated distance range $\bar{r}_i$ remains mostly the total of the original distance range then the NLOS error value, i.e., $\bar{r}_i = r_i + n_i$, and the estimated variance $\bar{\sigma} \gg \sigma$, $\bar{r}_i \gg r_i$.

The WLSE criteria find useful to determine the coordinates of the UT as given below equation 3.

$$(\check{x}, \check{y}, \check{z}) = \mathrm{argmin}_{x,y} \sum_{i=1}^{N} (\bar{r}_i - r)^2$$
$$= \mathrm{argmin}_{x,y} \sum_{I=1}^{N} \left(\bar{r}_i - \sqrt{(X_I - X)^2 + (Y_I - Y)^2 + (Z_I - Z)^2}\right)^2 \qquad (3)$$

The above equation is highly nonlinear with respect to the location of UTs, any variation from NLOS-free models have the worst estimate errors [21]. The identification of the LOS/NLOS station and elimination of the related range measurement is assumed as a solution to avoid the above-mentioned issues. The subsequent section designs an effective solution to address 3D indoor node localization problem to avoid the NLOS error.

Algorithm: OBSO-WLSE

Import swarm $X = [X_1, x_2, x_3, \dots x_D]$
Improve population velocity v
Ste step size, boundary speed and maximum iterations k
For (k>K)
Set inertia weight by using equation 13
Upgrade $\Delta_d(x, y)$ by using equation 14
While each search OBSO agent
Calculate $\hat{x} = (A^T W A)^{-1} A^T W B$
Update position using proposed heuristic algorithm
End while
End for
Calculate fitness function
Record the samples
For each agent
F(x)>f(best)
Update f(X*)
End for
Return $\omega_i \frac{1}{\sqrt{\alpha_i^2 + \beta_i^2}}$

The algorithm clearly explains about meta heuristic OBSO-WLSE technique, in which maximum iterations have been updated through agents at Node Localization.

3.2 Determining Target's Initial Location Using OBSO Algorithm

During the initial stage, the initial location of the targets is determined by the OBSO algorithm. Based on the swarm intelligent nature of beetles, the BSO algorithm is developed [22]. Here, every individual beetle defines a possible solution to the optimization problem, and every one represents a fitness value computed through the fitness function. Alike PSO algorithm, the beetles distribute information. The OBSO at 1st stage providing random solutions using iterations as well as at 2nd stage search agents has been imported, therefore population search and probability of dimensions can improve. However, the distance and direction of the beetle be algorithm can compute towards speed & data intensity rate. Fig. 2 illustrates the process of Beetle's optimization model [22, 23]. The proposed Beetle's optimization technique can provide target estimation which is show Mathematically, in below explanation. The beetle population of n beetles are denoted by $X = (X_1, X_2, \cdots, X_n)$ in an S-dimension searching area, where the ith beetle signifies S-dimension vector $X_i = (x_{i1}, x_{i2}, \cdots, x_{iS})^T$, characterizes the location of the ith beetle in the S-dimension searching space, & indicates possible solution towards the issue. The fitness function of each beetle location is calculated based on the goal function. The rate of the ith beetle can be defined by $V_i = (V_{i1}, V_{i2}, \cdots, V_{iS})^T$. The specific extremity of the beetle can be indicated by $P_i = (P_{i1}, P_{i2}, \cdots, P_{iS})^T$, and the group extreme value of the population can be denoted as $P_g = \left(P_{g1}, P_{g2}, \cdots, P_{gS}\right)^T$. This behavior can be mathematically modeled as [23]:

$$X_{is}^{k+1} = X_{is}^{k} + \lambda V_{is}^{k} + (1 - \lambda)\xi_{is}^{k} \quad (4)$$

where $s = 1,2,\cdots,S$; $i = 1,2,\cdots,n$; k is the present iteration. V_{is} is stated as the beetle speed, and ξ_{is} characterizes the upsurge in beetle position movement. λ is a positive constant. Next, the speed can be determined as in equation 4 and 5.

$$V_{is}^{k+1} = coV_{is}^{k} + C_1 r_1 \left(P_{is}^{k} - X_{is}^{k}\right) + C_2 r_2 \left(P_{gs}^{k} - X_{gs}^{k}\right) \quad (5)$$

where c_1 and c_2 are 2 positive constant parameters, and r_1 & r_2 are two arbitrary functions in the interval of 0 to 1. ω is the inertia weight.

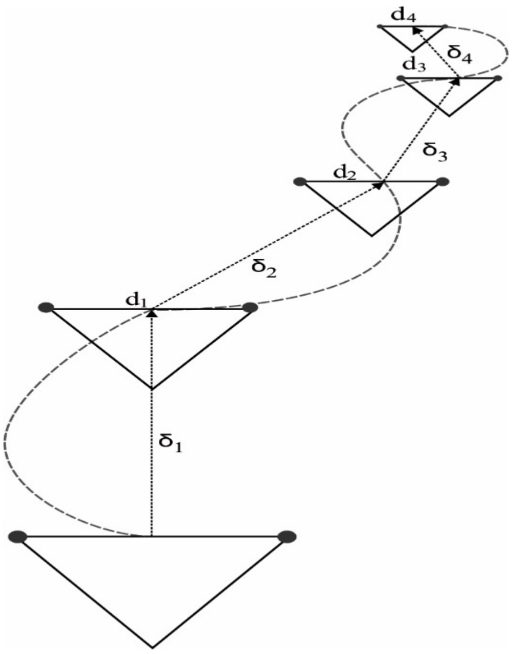

Fig. 2 - Process of Beetle's optimization

In this case, a mechanism of reducing inertia weight is determined using Eq. (6):

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{K} * k \quad (6)$$

Where ω_{min} and ω_{max} represents the lower and higher values of ω. k and K are the presents and highest iterations. Here, the extrema value of ω is fixed to be 0.9, and the minimum value is predefined as 0.4, thus the model searches a maximum range at the initial stage of the evolution and identifies the optimum solutions rapidly. Since the value of ω gets continually decreased, the speed of the beetle is reduced and entered into the local search. The ξ function represents the incremental function which can be determined using Eq. (7):

$$\xi_{is}^{k+1} = \delta^k * V_{is}^k * \text{sign}\left(f(X_{rs}^k) - f(X_{rs}^k)\right) \quad (7)$$

In this case, the step size is δ. Antennae on the right and left can be said to seek in the following ways shown in equation 8.

$$X_{rs}^{k+1} = X_{rs}^k + V_{is}^k * d/2$$
$$X_{rs}^{k+1} = X_{rs}^k - V_{is}^k * d/2 \quad (8)$$

The trajectory path of the swarm of beetles in a 2D and 3D spaces correspondingly. For the representation of the searching path in a highly visual way, small population size is employed and exhibited the position change process of 10 rounds in the 3D space. Due to the factors like step length and inertia weight coefficient gets decreased iteratively, the BSO algorithm does not convergences to the target rapidly and avoids the local optima problem. Fig. 3 demonstrates the flowchart of BSA technique.

In BSO algorithm, an arbitrary set of solutions are initialized [24][25]. Next, under every round, the searching agent will update the location depending upon the individual searching strategy and the optimum solution that presently exists. The integration of these two regions not only speeds upon the execution time it also reduces the possibility of trapping to local optima. Therefore, it is found to be consistent in handling high-dimensional problems. Exploitation and exploration are also possible capabilities of the BSO algorithm. Additionally, the algorithm's speed and accuracy are both improved, as is the algorithm's stability, by linearly integrating the search speed and accuracy. To further improve the performance of the BSO algorithm, OBSO algorithm is derived by incorporating the concepts of OBL.

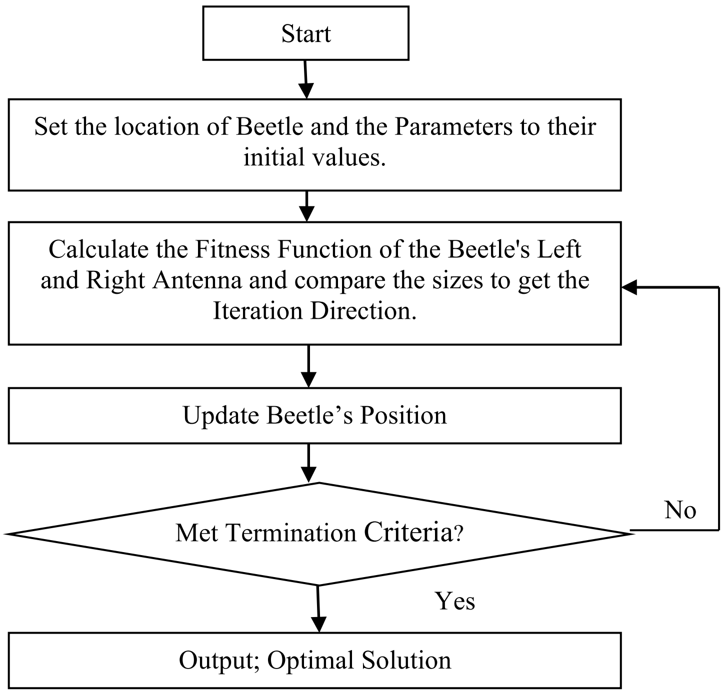

Fig. 3 - Flowchart of BAS algorithm

OBL signifies an optimization method that is utilized by several researchers for improving the quality of their initial population solutions by differentiating these solutions. In OBL approach works by search both methods in search space. These 2 methods contain one the original solution as another way is signified by their opposite solution. At last, the OBL approach obtains the fittest solutions in every solution.

Opposite number: x implies the real number over the interval $x \in [lb, ub]$. The opposite number of x represented by $\tilde{x}$ and to define their value Eq. (9) is utilized:

$$\tilde{x} = lb + ub - x \tag{9}$$

Eq. (9) is generalized for applying from the search space with multi-dimensions. So, to generalize it, all search agents position and their opposite position is expressed as Eqs. (10) and (11):

$$X = [X_1, x_2, x_3, \dots x_D] \tag{10}$$

$$\tilde{x} = [\tilde{x}_1, \tilde{x}_2, \tilde{x}_3, \dots \tilde{x}_D] \tag{11}$$

The values of every element $\tilde{x}$ is defined utilizing Eq. (12):

$$\tilde{x}_j = lb_j + ub_j - x_j \text{ where } j = 1,2,3, \dots, D \tag{12}$$

Optimization Based on Opposite population: During this method the FF is $f(.)$. So, when the fitness value $f(\tilde{x})$ of opposite solution is higher to $f(x)$ of their original solution x, after that $x = \tilde{x}$; otherwise $x = x$.

The process to integrate OBL with BSO technique is summarizing by the following:
Initialization the beetle positions X as x_i where $(i = 1,2, \dots, n)$.
To define the opposite positions of beetle population OX as $\tilde{x}_i$ where $(i = 1,2, \dots, n)$.
To choose the n fittest beetles in $\{X \cup OX\}$ and it is determined the new primary population of BSO.

3.3 Determining Target's Final Location Using WLSE Technique

At stage, the WLSE technique performs iterated computations rapidly to determine the precise final location of the target based on the initial location of the target derived by the OBSO algorithm. In real-time application, the localization process is influenced by several factors namely atmosphere, measure of unknown node to node distance d_i generally is superior to ideal measurement distance, it results in the coordinate point of the unknown nodes in the range rather than dot. At present for calculating the unknown node coordinates error is formed [26][27]. Here, the computation of unknown node coordinate points can compute the distance to all knowns is d_i, and introduce the principle for the sum of squares of the distance measured error shown in equation 13.

$$\Delta_d(x, y) = \sum_{i=1}^{n} W_i \left[\sqrt{(x - x_i)^2 + (y - y_i)^2} - d_i\right]^2 \tag{13}$$

Where $W_i$the weighting factor and n is is the beacon node. An erroneous summation of the squared of weighed $\Delta_d(x, y)$ squares must be generated in order to achieve the minimum of Δ_d carrying partial derivatives shown in equation 14.

$$\begin{cases} \dfrac{\partial \Delta_d(x, y)}{\partial x} = 0 \\ \dfrac{\partial \Delta_d(x, y)}{\partial y} = 0 \end{cases} \tag{14}$$

$W = \mathrm{diag}(w_1, w_2, \dots, w_n)$ is the positive fixed diagonal weighted matrix, and ordered as in equation 15 and 16.

$$\frac{\partial W(\hat{x})}{\partial(\hat{x})} = -A^T(W + W^T)(B - A\hat{x}) = 0 \tag{15}$$

$$\hat{x} = (A^T W A)^{-1} A^T W B \tag{16}$$

The WLSE technique is based on the condition to examine the environment and node among the positioning precision as well as ranging error [28][29]. By the utilization of the trilateral positioning model, if connected to the least square model for calculating the suitable weights to all beacon nodes are create the method to clearly enhance the localization accuracy [30].

The ranging error be proportional to the real distance, whereas the method's placement efficiency is proportional to the initial environmental interference. As a result, the weighed assigning of beacon nodes may be done based on the two categories of errors. Beacon node placement accuracy (x_i, y_i) is α_i range error is β_i and node weighting parameters areω_i. the following equation 17 is used to determine the weight.

$$\omega_i \frac{1}{\sqrt{\alpha_i^2 + \beta_i^2}} \quad (17)$$

The OBSO-WLSE model can extract locations at initial stage, later detect accurate location by using Node localization. Three-dimensional network can extract features of location using OBSO-WLSE technique. The detailed notes of algorithm have been presented at above 3.1 section discussion.

1) Determining the Value of ' α'

α is utilized for representing the node positioning error. A comparable environment can be created by randomly creating n beacon nodes, k unknown nodes, and beacon node coordinate points of (X_2, Y_2) ... ... (X_n, Y_n) After iterating through the beacon nodes coordinates of all locations by the initial coordinate variance d i of the unknown nodes for m times, the average error assigned to stays at m times (X_1, Y_1) and the unknown node coordinate points are (X, Y) shown in equation 18.

$$\alpha = \frac{\sum_{i=1}^{m} d_i}{m} \quad (18)$$

2) Determining the Value of ' β'

β is utilized for representing the node among the range error. Utilizing the testing space extreme 2 beacon nodes range error computation, the outcome is β. A & B are the experimental space extreme beacon nodes. Beacon node A expressed the right location to beacon node B based on values of 2 calculating nodes for computing the distance L; Utilize beacon node B for measuring the distance L_1 among the node A; compute the entire values that among distance as well as actual distance, and related to transmission radius of beacon nodes, become β shown in equation 19.

$$\beta = \frac{|L_1 - L|}{R} \quad (19)$$

R represents the beacon nodes transmission range.

4. Performance Validation

This section validates the presentation of the OBSO-WLSE model with other existing models in terms of distinct measures. Fig. 4 and Table 2 investigate the number of localized nodes (NLN) analysis of the OBSO-WLSE model under the presence of varying anchor nodes. The results portrayed that the OBSO-WLSE model has obtained effective performance by obtaining maximum NLN and it gets increased with an increase in number of anchor nodes. For instance, with the presence of 10 anchors, the OBSO-WLSE model has achieved a higher NLN of 131 nodes whereas the WLSE, M-BOA, GWO, ACO, & PSO algorithms have obtained a lower NLN of 115, 112, 105, 104, and 103 nodes respectively. Likewise, with the presence of 30 anchors, the OBSO-WLSE system has attained a superior NLN of 165 nodes whereas the WLSE, M-BOA, GWO, ACO, and PSO methods have achieved a minimum NLN of 143, 136, 131, 120, and 113 nodes correspondingly. Simultaneously, with the presence of 50 anchors, the OBSO-WLSE model has achieved a higher NLN of 190 nodes whereas the WLSE, M-BOA, GWO, ACO, and PSO methodologies have reached a lesser NLN of 168, 152, 150, 141, and 132 nodes correspondingly. The following node architecture is modelled on MATLAB software via Ns3 tool box. The all-training data samples have been collected from Kaggle ImageNet object file as well as real time samples has been collected from KL university, Guntur.

Table 2 - Anchors Counts (AC) and no. of nodes analysis

AC	OBSO-WLSE(OBW) Proposed	WLSE (WSE) [13]	M-BOA (MOA) [14]	GWO (GO) [10]	ACO [11]	PSO [12]
10.00	131	115	112	105	104	103
20.00	143	129	118	118	116	106
30.00	165	143	136	131	120	113

40.00	170	154	141	140	134	120
50.00	190	168	152	150	141	132

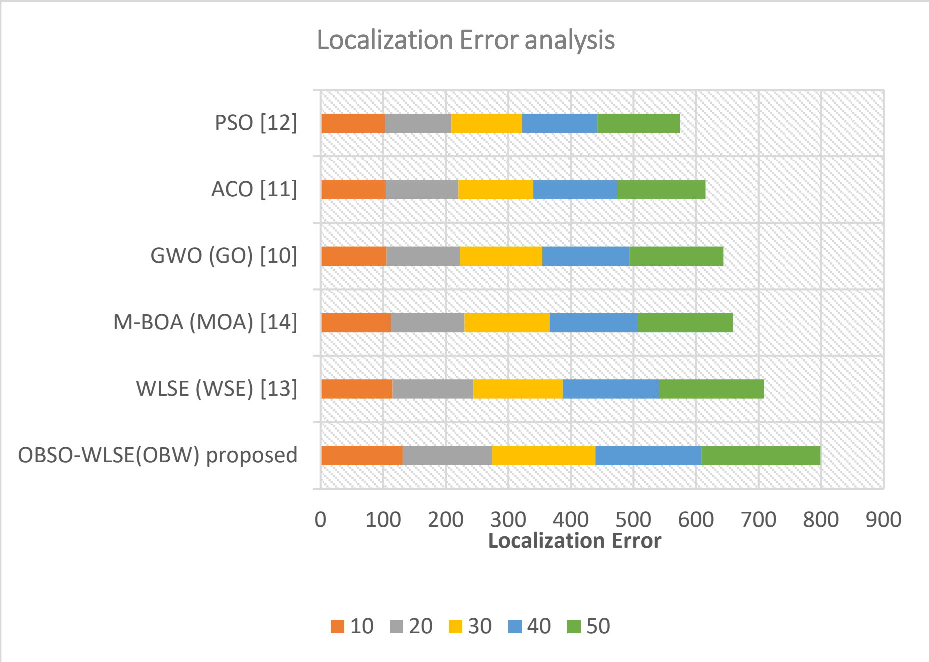

Fig. 4 - Number of localized nodes analysis of OBSO-WLSE model

An analysis of localization error obtained by the OBSO-WLSE model with state of art methods takes place in Table 3 & Fig. 5 under distinct anchor nodes. The experimental results indicated that the OBSO-WLSE model has resulted in a minimum localization error (LOE) and it tends to decrease with a rise in anchor node count. For example, when ten anchors are present, the OBSO-WLSE model achieves the lowest LOE rate of 0.339, whereas the WLSE, M-BOA, GWO, ACO, & PSO algorithms achieve higher localization error rates of 0.420, 0.517, 0.605, 0.679, and 0.701, respectively. Furthermore, the OBSO-WLSE strategy achieved a minimal LOE of 0.219 in the presence of 30 anchors, while the WLSE, M-BOA, GWO, ACO, and PSO approaches achieved rates of 0.360, 0.447, 0.505, 0.519, and 0.541, respectively. Additionally, the OBSO-WLSE approach achieved a minimal localization error (LOE) of 0.139 in the presence of 50 anchors, while the WLSE, M-BOA, GWO, ACO, and PSO techniques achieved greater localization error rates of 0.280, 0.367, 0.475, 0.549, and 0.481, respectively.

Table 3 - LOE vs. No. of Anchors Counts (AC)

AC	OBSO-WLSE(OBW) Proposed	WLSE (WSE) [13]	M-BOA (MOA) [14]	GWO (GO) [10]	ACO [11]	PSO [12]
10.00	0.339	0.420	0.517	0.605	0.679	0.701
20.00	0.279	0.380	0.467	0.595	0.659	0.691
30.00	0.219	0.360	0.447	0.505	0.519	0.541
40.00	0.179	0.330	0.397	0.465	0.559	0.511
50.00	0.139	0.280	0.367	0.475	0.549	0.481

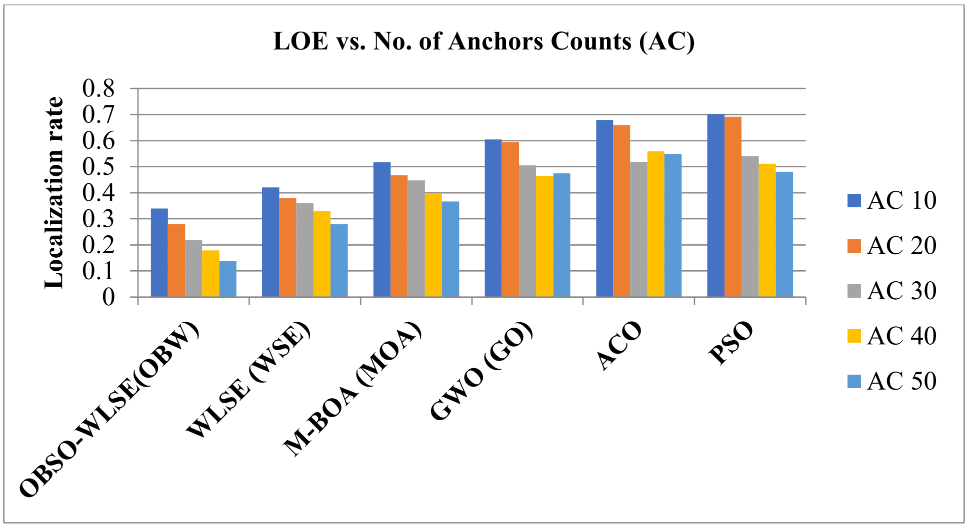

Fig. 5 - LOE analysis of OBSO-WLSE model

Table 4 & Fig. 6 compare the OBSO-WLSE model's localization effectiveness by other known approaches when the number of anchor nodes is varied. From the table, it is obvious that the OBSO-WLSE model has resulted in an improved localization performance with the maximum localization rate. The rate of localization needs to be high for better performance and it gets increased with an increase in anchor node count. For instance, through the existence of 10 anchors, an increased localization rate of 0.655 has been accomplished by the OBSO-WLSE model whereas the WLSE, M-BOA, GWO, ACO, and PSO algorithms have exhibited a degraded localization rate (LOR) of 0.575, 0.560, 0.525, 0.520, & 0.515 respectively.

Table 4 - LOR vs No. of AC

AC	OBSO-WLSE(OBW) Proposed	WLSE (WSE) [13]	M-BOA (MOA) [14]	GWO (GO) [10]	ACO [11]	PSO [12]
10.00	0.655	0.575	0.560	0.525	0.520	0.515
20.00	0.715	0.645	0.590	0.590	0.580	0.530
30.00	0.825	0.715	0.680	0.655	0.600	0.565
40.00	0.850	0.770	0.705	0.700	0.670	0.600
50.00	0.950	0.840	0.760	0.750	0.705	0.660

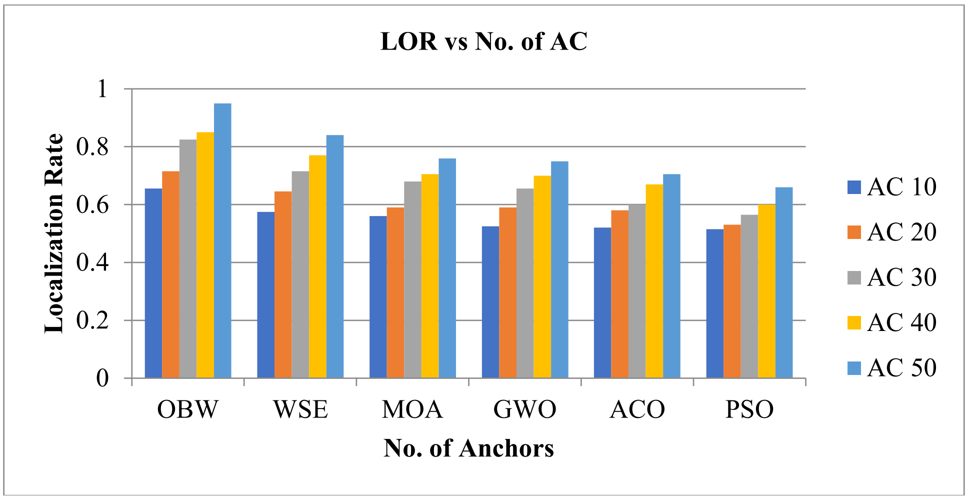

Fig. 6 - Localization rate analysis of OBSO-WLSE model under varying anchor node count

Eventually, with the existence of 30 anchors, an improved localization rate of 0.825 has been accomplished by the OBSO-WLSE method whereas the WLSE, M-BOA, GWO, ACO, and PSO technique have demonstrated a degraded localization rate of 0.715, 0.680, 0.655, 0.600, & 0.565 correspondingly. Meanwhile, through the existence of 50 anchors, an increased localization rate of 0.950 has been accomplished by the OBSO-WLSE approach whereas the WLSE, M-BOA, GWO, ACO, and PSO techniques have showcased a degraded localization rate of 0.840, 0.760, 0.750, 0.705, & 0.660 correspondingly.

Table 5 - Gives a detailed LOE analysis of the OBSO-WLSE model by other existing methods under varying error rates and transmission ranges

Error (%)	OBSO-WLSE(OBW) Proposed	WLSE (WSE) [13]	M-BOA (MOA) [14]	GWO (GO) [10]	ACO [11]	PSO [12]
5.00	00.290	00.410	00.460	00.620	00.660	00.680
10.00	00.230	00.380	00.430	00.600	00.620	00.660
15.00	00.170	00.360	00.440	00.480	00.540	00.580
20.00	00.120	00.350	00.380	00.470	00.480	00.540
25.00	00.100	00.320	00.340	00.420	00.450	00.500
Transmission Range	**OBW**	**WLSE**	**MOA**	**GWO**	**ACO**	**PSO**
10.00	00.140	00.340	00.357	00.485	00.509	00.551
15.00	00.100	00.240	00.307	00.435	00.469	00.491
20.00	00.080	00.210	00.307	00.385	00.459	00.521
25.00	00.050	00.120	00.247	00.365	00.379	00.411
30.00	00.040	00.140	00.227	00.265	00.359	00.431

Table 5 Range Error & Transmission Range (m) vs LOE were analyzed in this study. An examination of localization error achieved by the OBSO-WLSE method with state of art methods occurs in Fig. 7 under different error rates. The experimental outcomes referred that the OBSO-WLSE system has resulted in a minimal LOE and it tends to reduce with a rise error rate. For instance, with an error rate of 5%, the OBSO-WLSE approach has attained a worse LOE of 0.290 whereas the WLSE, MOA, GWO, ACO, & PSO technique have achieve improved LOE rates of 0.410, 0.460, 0.620, 0.660, also 0.680 similarly. Along by that, with an error rate of 15%, the OBSO-WLSE system has achieved the worst localization error of 0.170 whereas the WLSE, M-BOA, GWO, ACO, & PSO method have achieve higher LOE rates of 0.360, 0.440, 0.480, 0.540, & 0.580 correspondingly. In line, with the error rate of 25%, the OBSO-WLSE model has attained a minimum localization error of 0.100 whereas the WLSE, M-BOA, GWO, ACO, & PSO methodologies have accomplished maximum LOE rates of 0.320, 0.340, 0.420, 0.450, & 0.500 respectively.

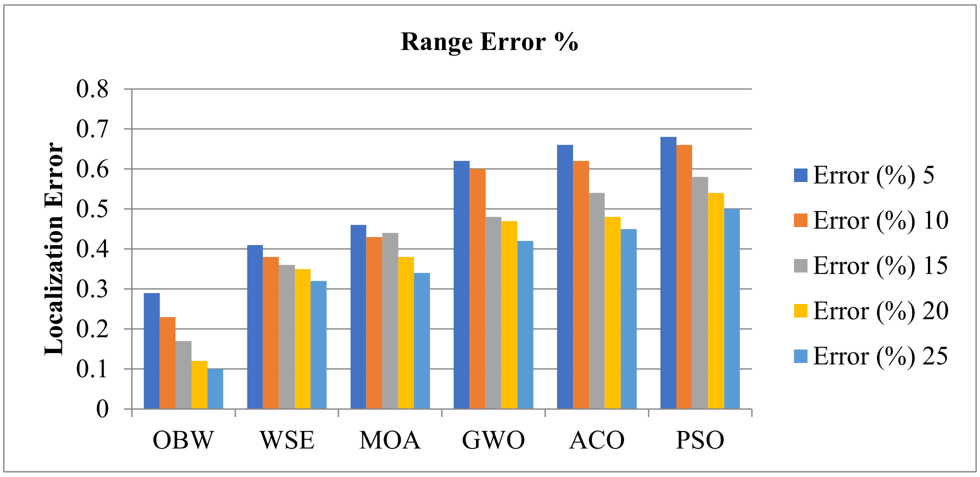

Fig. 7 - LOE analysis of OBSO-WLSE model in error range

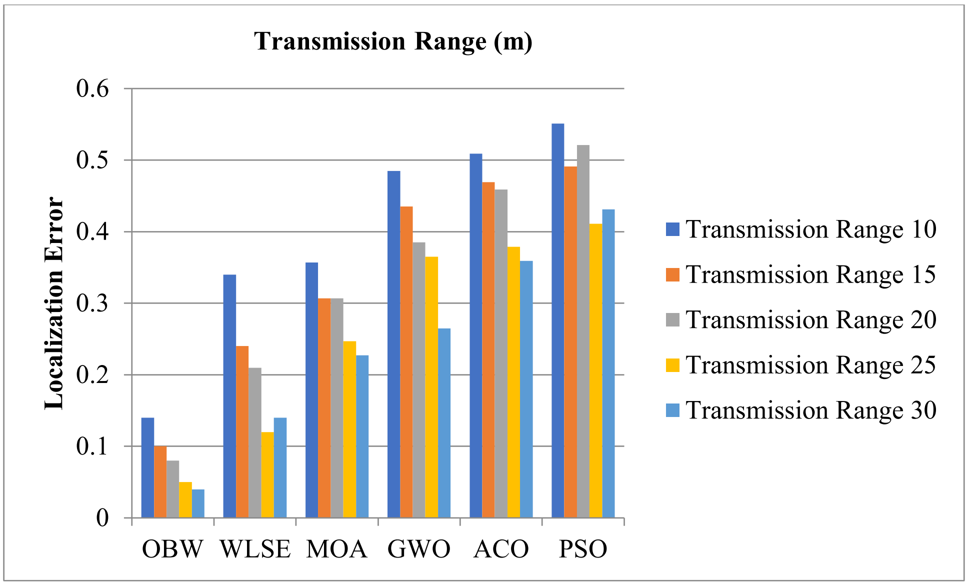

Fig. 8 - Localization error analysis of OBSO-WLSE model in transmission range

An investigation of localization error reached by the OBSO-WLSE model with state of art methods take place in Fig. 8 under various transmission ranges. Testing indicated that OBSO-WLSE results in minor localization errors, and this error decreases as the transmission range increases. As an example, with a transmission range of 10 meters, the OBSO-WLSE strategy has achieved the lowest localization error of 0.140 compared to the WLSE (0.357), M-BOA (0.485), GWO (0.509), and PSO (0.551) techniques. While the OBSO-WLSE model achieved the lowest localization error of 0.080 at a transmission range of 20 m compared to the WLSE (0.0210), M-BOA (0.307), GWO (0.459), and PSO techniques (0.521) at the same distance. A 30-meter transmission range yields the lowest localization error, whereas the GWO, M-BOA, ACO, & PSO approaches all have better transmission ranges of 0.227, 0.359, and 0.431, respectively, in comparison shown in fig 7 and 8.

5. Conclusion

The OBSO-WLSE algorithm has been used to propose a successful 3D Indoor Node Localization Technique. Primarily, node deployment and network initialization processes have been carried out. When the initialization process gets completed, the OBSO-WLSE algorithm is performed towards determines the actual indoor positioning of the nodes. The OBSO-WLSE algorithm operates on two major phases namely determining the initial location of the targets using OBSO algorithm and determining the final location of the targets using WLSE technique. The performance of the OBSO technique can be improved by the integration of OBL into the traditional BSO algorithm. A number of indicators were conducted and highlighted the betterment of the OBSO-WLSE method in terms of localization error, range error and transmission range. Therefore, proposed OBSO-WLSE model has found to be an effective method for 3D-indoor localization technique and can be utilized in real time environments. In future, the energy efficient clustering techniques can be incorporated into the proposed method to reduce the overall energy consumption and load balancing.

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