COMPARATIVE STUDY USING META HEAURISTIC ALGORITHMS ON NODE LOCALIZATION WITH UWB NETWORK FOR RANGEBASED AND RANGE FREE ENVIRONMENTS

Yedida Venkata Lakshmi [1] Parulpreet Singh [2]

1. Research scholar,School of Electronics and Electrical Engineering, Lovely Professional University, Phagwara, Punjab, India.
E.mail id: venkatlaki@gmail.com

2. Associate Professor, School of Electronics and Electrical Engineering, Lovely Professional University, Phagwara, Punjab, India.
E.mail id; parulpreet.23367@lpu.co.in

Abstract: Optimization of node localization to check the mobility of network in interior and exterior environment is a need of getting security concern nowadays in the entire world. UWB-based WSN network is one of the better choices where regular network issues are raising. In this context, accuracy is key in finding the exact node location with a low error rate. Network topology is increasing its criteria daily, and algorithms with accuracy become research criteria in both environments. The present work is a comparative study on enhanced algorithms with PSO-based optimization techniques of different methods. The proposed algorithm results are compared with the literature on different algorithms to verify the decrement in localization error. Ensemble and back-propagation techniques added with PSO gave good results compared to regular PSO methods discussed.

Key words: Accuracy, Node Localization, UWB, PSO, Hearustic Algorithms

1.0 Introduction

In the widespread use of WSNs, coverage is a major concern. The distance between the target and the nearest sensor node would be a critical factor in any coverage model. As a result, sensor node locations provide the foundation for algorithms that evaluate network reachability [1]. A key component of location-based routing (LR) systems is the location data collected by sensor nodes. Two main benefits of LR protocols are scalability and reduced overhead due to topology changes [2]. In addition, location-aided routing (LAR) uses location data to acquire a more condensed request zone than would otherwise be possible while looking for routing paths. It has been shown in recent studies [3] that the LAR protocol can compete with the shortest path routing method even when only a simple anchor-free localization technique is used. Geographic addressing is a method for identifying and communicating with devices in a network based on their geographical location rather than their IP address. Most applications in modern WSNs, beyond the networking protocols themselves, rely on geolocation data to make sense of sensory data collected in various areas. For instance, location data plays a crucial role in context reasoning [4], especially in intelligent settings. There are organised literature reviews [5, 6] on sensor localisation. The vast majority of these works present preliminary findings on sensor localization or location techniques borrowed from cellular networks or robots. This study provides a detailed review of the state-of-the-art methods for determining the location of sensor nodes in a WSN. The term "localization" throughout the study will refer to sensor localization unless otherwise specified. A collection of feature pairs may also characterize localization systems. Different schemes use different methods to gather data. Indoors, outdoors, in a 2-D or 3-D world, the nodes could be stationary or mobile. It can sometimes be made clear if specific tools are needed for location measurements. Many subjects, including mobile ad hoc social networks and opportunistic mobile networks, are covered in the numerous articles produced by Liu et al. [5,6]. This study focuses on WSNs, which, in contrast to their network, employ a swarm of sensors to keep tabs on a specific region. Many localization methods, most of which use a flat sensing region and rely on recent years, have been given. Because of this, designing WSNs' three-dimensional localization systems presents significant challenges.Combining the Symbiotic Organism Search (SOS) algorithm with multi-group communication and quantum behaviour methods, Chu et al. [7] developed a novel global optimization approach they term the Symbiotic Organism Search Algorithm with Multi-Group Quantum-Behavior Communication (MQSOS). It is fast and convergent, making it a viable tool for resolving real-world problems that call for consideration of various arguments. Liu et al. [8] methods were developed to achieve node localization based on distance data between neighbouring nodes. They conduct experiments to show that the suggested algorithms improve upon prior methods in terms of confinement precision and energy consumption. Distributed localization nodes, according to Kotwal et al. [9], Determine their minimum and maximum distances from anchor nodes using RSSI. The approximation is performed using a straightforward binary search technique. The approximate distance restrictions are helpful when determining the node's viability concerning anchor nodes. In order to minimise localization errors, an optimization problem is posed, and the coordinates of the feasibility region are used as seed particles in a particle swarm optimization solution (PSO). Low et al. [10] If the identity of the emitter nodes is unknown, please describe a mechanism for determining their physical location. The idea is based on the fact that there are four anchor nodes whose locations are already established and that there are also one or more unknown nodes transmitting radio frequency signals that the four established nodes can pick up. The technique is flawed since it relies solely on an artificially generated measure of signal strength. Wang et al. [11] Develop an innovative coupling technique based on Bacterial Foraging Algorithm (BFA) and Glowworm Swarm Optimization (GSO). Verified by CEC2013 benchmarks, the algorithm's optimization performance has a high convergence rate. According to the trilateration method, the estimated distance between the reference and target nodes deployed in the field can be measured with the help of the relative signal strength indicator (RSSI) method. Graefenstein et al. [12]. Sumathi et al. [13] suggested using a single anchor node in conjunction with RSS to find unknown nodes. In this study, we introduce a least squares approach to pinpointing predetermined target nodes. Perpendicular intersection (PI), created by Guo et al. [14], is a mobile-based approach that does not directly map RSS distances. Node positions are determined using the geometric PI ratio. Shi et al. [15] presented a method in which a single mobile anchor communicates with the network's sensor nodes via ultra-wideband (UWB) transmissions. Wang et al. [16] presented the Distance Vector-Hop dependent method for pinpointing sensor nodes. This algorithm's failure is mostly attributable to its high complexity and cost. To enhance the performance of 3D localization, Xu et al. [17] suggested a method that combines DV-Distance with the quasi-newton optimal methodology. The proposed algorithm was further tested to ensure its efficacy by evaluating its localization accuracy and coverage. It was suggested to use an irregular RSSI model for 3D localization in WSNs. by Li et al. [18]. This model was proposed by the authors as a means of quantifying the connection between DOIs and the range variability in signal transmission. Ahmad et al. [19] suggested a parametric loop-division technique for 3D localization when the deployed sensors are placed within a region surrounded by a community of anchor nodes. This method effectively reduces the size of the network in the direction of the centre and yields good localization results. Gopakumar et al. [20] a novel, reduced, and computationally efficient swarm intelligence approach to finding stationary nodes was developed. Using a PSO-based strategy, Chuang et al. [21] easily find sensor nodes using the RSS ranging technique. The technique is more effective at localization. Kulkarni et al [22,23] PSO-Iterative algorithm for decentralized iterative localization. When there are more than three anchors for a specific target node, localization errors can be reduced with PSO. Both the range-free HPSO and the range-free BBO localization techniques Kumar et al. [24] that need less hardware resources. It uses PSO and BBO algorithms to optimize the edge weights. Finding the best spot for uncharted sensor nodes requires optimization. Arora et al. [25] proposed performing the BOA optimization programme. PSO and FA are evaluated alongside BOA in 2D benchmarking settings. Their solution surpasses competing meta heuristic algorithms in terms of convergence time and accuracy. The standardization of range-based approaches has led to their widespread adoption, but the greater uncertainty introduced by flip uncertainty has limited their utility. Computational intelligence algorithms based on PSO have been proposed for locating target nodes that are in motion in WSNs [26-30]. The technique is implemented in two phases, with anchor nodes located at the four corners of the sensing area. In the first stage, RSSI distance calculations were performed. The idea was that, in a later stage, virtual anchor nodes may use the anchor to find other nodes. Centroid calculations are obtained in these phases using a technique called PSO for optimization, and the outcomes show a reduced convergence time.

2.0 Methodology of proposed work

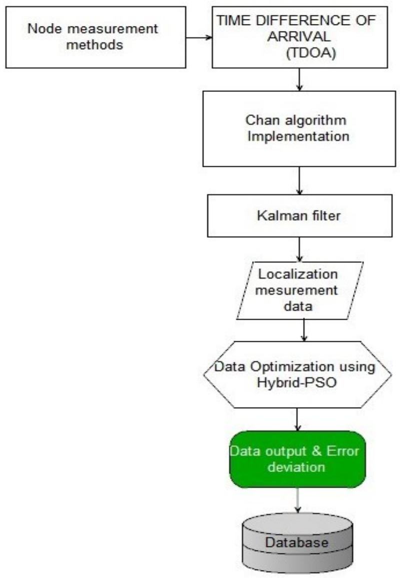
Measuring methods for the range based indoor localization taken as least square for 2D and Tetra hydron for 3d measurement. Improved Chan algorithm with PSO taken as primary accuracy measurement. Optimization improved with the ELPSO, and BPNN-PSO to check the localization error. For range free localization an improved 3D measurement along with least square used to estimate the position using DV-HOP. Different DV-HOP methods CC DV-HOP, HYBRID DV-HOP, and SEQUENTIAL DV-HOP used to compare the accuracy of measurement. PSO-S DV-HOP and EMPSO implemented for PSO hybridization. Work compared with the H-PSO and BBO to evaluate the localization error. Kalman filter used in both environments for noise accuracy.

2.1 Proposed algorithms for Range based

The effectiveness of tried-and-true methods is conditional on the specific localization technique and controller setup used. In this study, we introduce hybrid algorithms to improve following TDOA measurements, which increases the precision with which UWB localisation may be applied indoors. Due to the constraints of physical equipment and challenges, there is a significant discrepancy between the measured and real targets. This research tries to close the chasm by improving the communication process in stages. The existing system of localization assumes the distance between the beacon and the target nodes by using TDOA parameters. As an added bonus, a refined Chan algorithm is used to determine the 2D and 3D locations of target nodes. After that, ELPSO, BPNN is used to fine-tune the predicted locations of target nodes.

The fundamental purpose of this study is to create a location-tracking and communication system based on a wireless sensor network that uses Ultra-Wideband technology. Distance estimation and tracking methods are also evaluated at the system level, taking into account objective mobility, functional design, strategic communications, and position update latency. A whole 10 m × 10 m standard environment was used for the simulations and measurements, which was the top floors of an office building. Fig. 1 demonstrates where the cabin beacons are deposited.

When developing an effective NLOS detection model, data from the real world is required, as it contains varying degrees of multipath effects and range errors. For this research, we used the LOS and NLOS data sets from the EWINE UWB LOS and NLOS datasets to inform our model. This information was gathered using a pair of Ultra-Wideband (UWB) Channel 2 receivers, with a centre frequency of Fc 3.9936 GHz and a bandwidth of B 499.2 MHz. Therefore, preamble lengths of up to 4096 bytes improved the average accuracy of first-path signal recognition.



Algorithm: Target Node location

1. Input: define objective function (LS/ Tetrahedron)
2. Output: Localization data
3. Initialize: anchor placement-P
4. Number of targeted nodes-N
5. Define localization measured co-ordinates (x_i, y_i) (x_i, y_i, z_i)
6. Activate sensor nodes (anchors)
7. For i= least co-ordinate
8. For anchor $P_i \approx$ check the least value of target
9. If P<Pi, then fix the value.
10. If not repeat steps 5,6,7
11. Run for the least coordinate Pi
12. End if
13. Evaluate
14. Update for measured values
15. End for
16. End.

Figure: Localization flow chart and measurement algorithm

Enhanced PSO has replaced standard PSO, recalculating measurements for node localization via Ensemble learning. Using a population of particles spread out at random in the parameter space, the Basic PSO approach attempts an optimal solution. The location of particles in the parameter space is indicative of different approaches to the design optimization problem. A particle's speed is determined by its position and its path in parameter space. Fewer parameters, faster convergence, and less gradient information are just a few of the many benefits of the PSO technique. Algorithm 3 analyzes a swarm of massless particles to determine the best possible spot. Swarms of particles with randomly chosen starting positions are used by the enhanced PSO method to find a collection of solutions that are both possible and desirable inside the search space. By adopting a bounding box technique, our proposed methodology condensed the initial search space.

Algorithm: Optimization using PSO

1. %% Output: the initial calculated value of the target position (x,y,z)
2. For $1 \leq i \leq N$ Do %% i is each particle
3. Initialization of particles
4. End
5. Do
6. For $1 \leq i \leq N$ Do
7. If fitness (X_i) > p-best i Then p-best-i = X_i;
8. End
9. If %%p-best-i is the best position of $^{i\text{-th}}$ particle

10. End
11. For g-besti=opti{p best$_i$i$_1$≤i≤N}%% optimum value
12. For 1 ≤ i ≤ N Do
13. If fitness (X_i) > p-best i Then p-best-i = X_i;
14. Update particle velocity and position according to the equation-9
15. If pbesti>gbesti
16. Then g best i = p best i;
17. End if
18. End for
19. End.

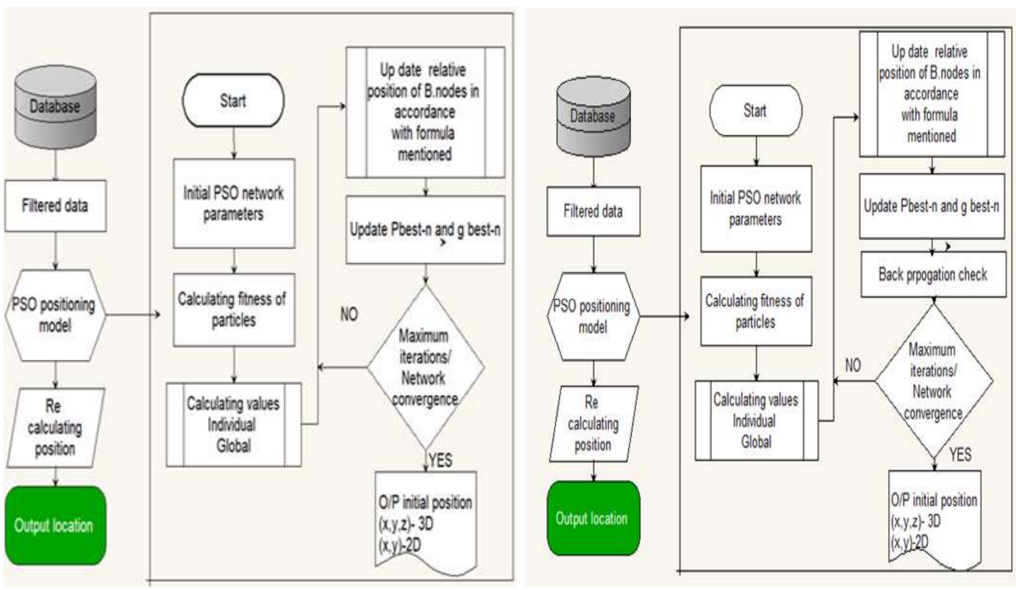


Figure: Implementation of both methods EMPSO and BPNN

3.0 Range free UWB environment implementation

In the present work anchor node-based measurement in the selected 20mx20m at range free maximum distance of 100 m with moving beacons of 30. A dynamic node movement-based environment considered to check the position of beacons using Least square and 3D positioning methods. Improved methods of Hybrid DV-HOP checked with traditional and CC- DV-HOP methods along with optimization with improved PSO method adopted for the present research.

The online sequential DV-HOP algorithm, depicted in Figure 1, proposes to use the least square approach to compare the distance between anchor node N and the next three anchor nodes in the series along a given line. After deployment with unidentified nodes, an average HOP count was collected. To find the unknown nodes in range-free localization, UWB-based RSSI relies more on the node's deployment and mobility.

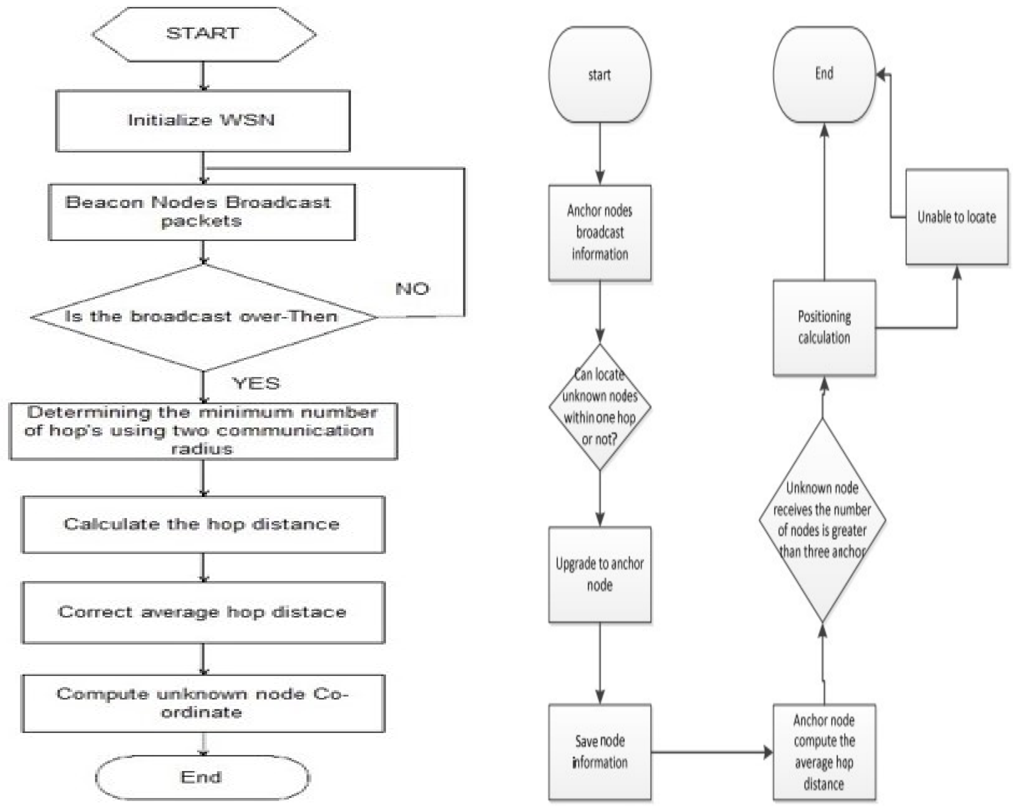


Figure: Proposed work flow chart with DV-HOP

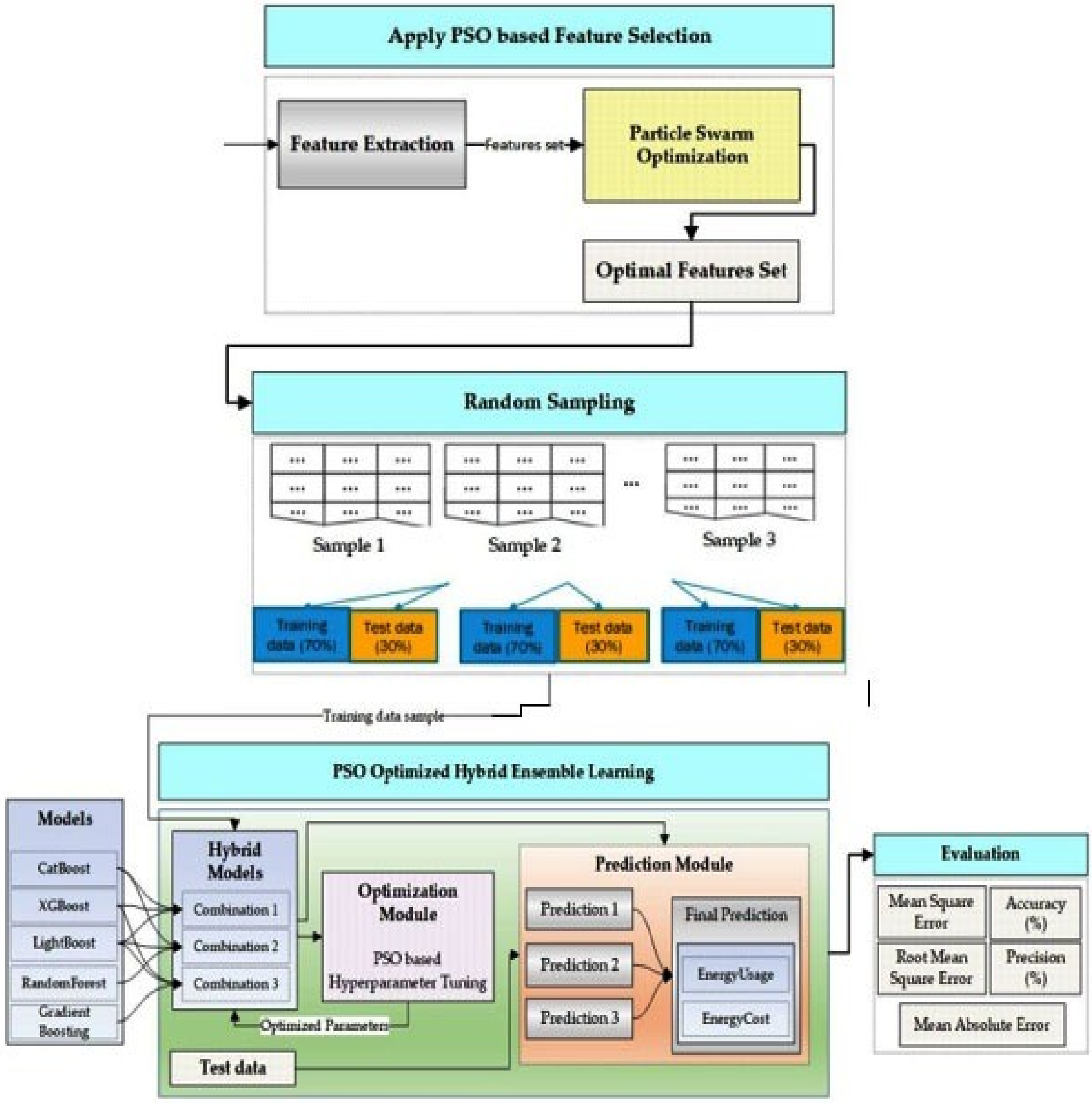
Hybrid DV- HOP algorithm (proposed)

Input:	WSN: Anchor nodes and their coordinates (x_i,y_i) where i=1..Na,Na: Anchors Population size;
Output:	Position estimate X_m of *m*= unknown sensor nodes
(1)	**Begin**/*Initialization
(2)	$X_{m(o)}$=0/ *initial position of unknown node to estimate
(3)	S=λ*i/*covariance matrix S, where 'i' is the identity matrix ; λ is a very large positive number
(4)	Locate nodes that can be used as anchors in the position estimate process.
(5)	**While** (at least one of nodes is not localized) **Do**
5.1	Computation of the minimal HOP count between selected anchors available for localization

5.2	LS (Least square method) and polynomial approximation can be used to minimize the HOP count to the optimal distance.
5.3	An algorithm 1 for determining the least number of hops between a given anchor and an unknown node.
5.4	Use the polynomial approximation to calculate the distance between anchors(i) and unknown nodes. (*j*): $d_{ij} = \propto_0+\propto_1 h_{ij}+\propto_2 h_{ij}^2$
5.5	The polynomial approximation may be used to estimate the distance b Positions estimations Xm of unknown nodes.. $X_{k+1}= X_k+ S_{k+1}A^T{}_{k+1}(B_{k+1}- A_{k+1}X_k)$
(6)	End while;
(7)	X_m/ *Estimated position of all unknown nodes m
(8)	End;

3.1 EM- PSO Based optimization

The proposed optimum solution approach integrates random sampling, feature selection, and ensemble learning. Both feature selection and optimising hyper-parameters are made easier with PSO in this research, according to it's a dual position as an optimization tool for ensemble predictions. The reduction of anchor nodes, correction of the average hop distance, and implementation of the PSO algorithm all contribute to the increased computational complexity of the EMPSO-DV-HOP relocation algorithm proposed. Using the PSO optimization technique, node coordinates result in a computational complexity proportional to the maximum number of iterations and the particle size. Time complexity decreases when the anchor node with the most considerable inaccuracy is removed and n is rectified. This makes the calculation reasonably accurate.



4.0 Results and Discussions

In performance compared to other popular algorithms, this one was found to be more accurate and consume less power. This research does not prove the efficacy of the proposed sensor node localization algorithm. However, it shows it can provide a solid foundation for finding where wireless sensor networks (WSNs) use 3D UWB indoor localization, an extension of 2D. Based on the findings, there is clear room for improvement in terms of the conditions under which anchors are placed. The node's dynamic momentum will shift randomly, and the Chan algorithm's measurement and filtering will be used in conjunction with swarm optimization methods. With anchors, it is important to find all the position errors in centimeters under dynamic situations to get an accurate reading. To accomplish localization, a group of unidentified nodes must make distance estimates between themselves and a set of three known anchors. Using a signal's received strength indicator, the distance to a previously unidentified node can be determined (RSSI). To find the best solution rapidly, PSO usually converges on it early, which causes it to get stuck in a local optimization level.

TABLE III

CO-ORDINATE VALUES OF LOCALIZATION OF 3D POSITIONING

Optimal technique – method	M.P	Transmission Range	Max localization Error-cm	Min localization Error-cm	Average LE cm	Total number of located nodes
ELPSO-(T)	1	100M	3.964	0.4320	1.75	50
	2		3.2462	0.3214	1.51	
	3		2.8654	0.2862	1.32	
	4		3.4632	0.4938	1.56	
ELPSO-(LS)	1	100M	4.2365	0.3164	1.91	50
	2		4.6432	0.3458	1.86	
	3		3.7564	0.3244	1.72	
	4		3.2146	0.3564	1.46	
PSO-BPNN-(T)	1	100M	3.8492	0.2654	1.82	50
	2		3.3291	0.3216	1.58	
	3		2.9654	0.2196	1.37	
	4		2.2132	0.2456	1.04	
PSO-BPNN-(LS)	1	100M	4.4263	0.3165	2.12	50
	2		3.6419	0.3427	1.68	
	3		2.9465	0.2696	1.42	
	4		2.7222	0.2421	1.28	
GBNN-PSO REF (33)	1		18.20	10.40	13.8	
	2		9.78	7.32	8.46	

	3	100M	3.50	1.37	2.72	50
	4		6.42	3.83	5.22	
NN-MODEL REF (34)	1	100M	10.0	5.8	7.4	50
	2		16.1	9.4	12.0	
	3		10.7	7.4	9.2	
	4		14.2	8.6	11.2	

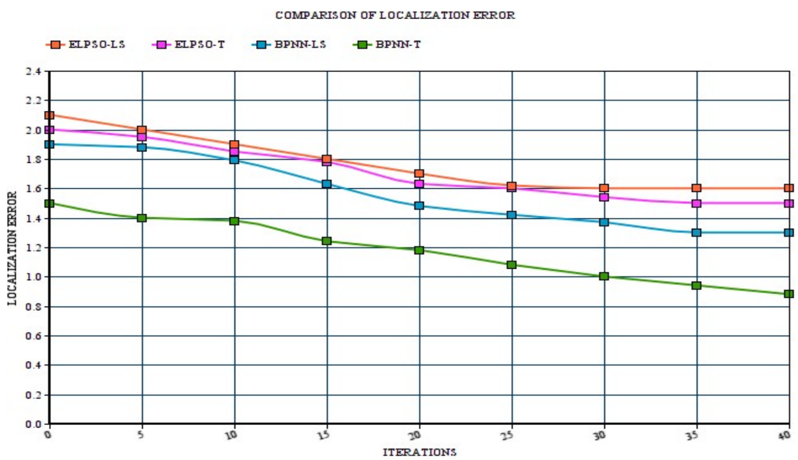


Figure:Comparison of localization error for all optimal techniques in centimeters.

Considering a back propagation neural network, as shown in figure 15 and described in table III, yielded the lowest error localization values in 3D. The proposed method resulted in relatively small values, with a minimum variance of 1.02cm. Hybrid 2D/3D algorithms using UWB networks for indoor localization and positioning have shown promising results, leading to the dynamic interpretation of measured values.

4.1 Range free results

DV-Hop and DV-Hop-based enhancement algorithms are analysed for their performance primarily in these results. The MATLAB simulator was used to test and investigate all of the proposed algorithms for localization faults and accuracy. UWB range-free wireless networks may now be located more effectively thanks to an improved PSO algorithm. From 10% to 20% and 20% to 50%, respectively, the number of anchor nodes and the wireless transmission distance change between samples.

Table 1 Various parameters applied in each figure the experiment ten times with uniformly distributed random node locations for each simulation.

No. Of Nodes	Anchor rate	Transmission range	Environment dimension
30	10% to 50%	Variable	100mtsx100mts
30	variable	Up to 50mts	100mtsx100mts

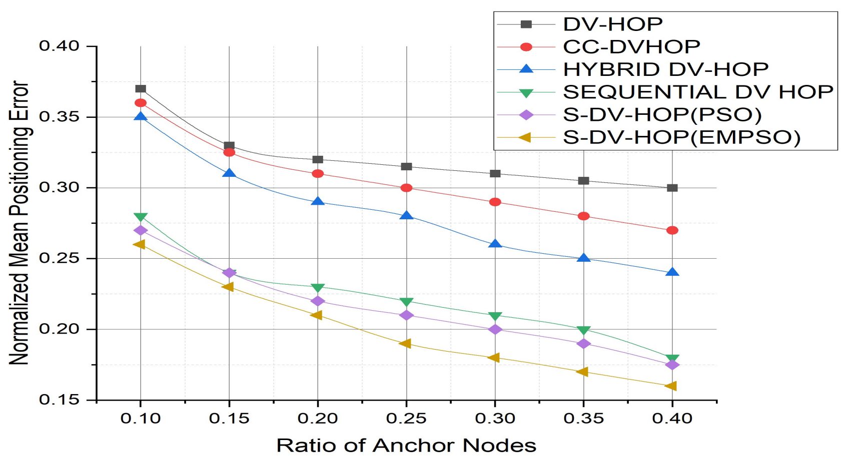


Figure: Mean position error vs anchor nodes ratio

Table: Comparison of meta heuristic algorithms with EM PSO

Algorithms	Number Of movements	Localization -error Max	Localization -error Min	Average LE	Number of targets
PSO	1	393.58	5.54	99.58	30
	2	533.79	8.31	98.37	30
	3	501.08	8.00	92.67	30
	4	513.25	8.12	96.12	30
HPSO	1	312.04	10.44	48.76	30
	2	501.34	6.47	40.32	30
	3	482.7	9.46	55.46	30
	4	571.24	18.22	55.32	30

BBO	1	585.14	18.22	125.6	30
	2	589.12	33.12	115.8	30
	3	563.16	15.28	128.1	30
	4	535.25	19.11	119.1	30
FA	1	611.01	19.22	22.23	30
	2	631.10	19.33	23.12	30
	3	6.89.12	34.12	24.65	30
	4	690.36	20.10	22.01	30
S-PSO	1	20.68	12.33	13.21	30
	2	19.89	12.06	12.24	30
	3	19.70	11.76	13.09	30
	4	18.62	10.3	12.46	30
EM- PSO	1	9.96	7.08	6.31	30
	2	9.49	6.3	6.87	30
	3	9.8	6.57	6.42	30
	4	9.76	6.45	6.64	30
For all above comparisons NP(Number of Population=30), Iterations 100, D(dimensional estimation= 3)					

6.0 Conclusions

This novel learning method enhances indoor location precision and aids particles in creating a more optimal and productive search region. The current method employs MATLAB for interior location detection and may be used for 2D and 3D ultra-wideband (UWB) systems. Furthermore, a MATLAB-based computational engine can manage the transmitter and receiver. Constant refinement of sound waveforms and associated reception filters can match the monitoring environment's dynamic nature. The Chan algorithm's low computational cost and high reliability make it ideal for tracking fast-moving targets in wireless sensor networks where many anchor nodes are not uniformly distributed. Hybrid techniques, including Ensemble learning and Back-propagation neural network, are used in Chan's localization algorithm based on the Kalman filter for PSO-based optimization. Among all the hybrid combinations tested, PSO combined with a

Back propagation neural network produced the best precise localization results. After running simulations, we found that PSO-BPNN using a 3D tetrahedron had the best performance in Constance values. The typical error is 2.72 centimeters, which is quite a bit. Our optimization technique reduces the minimum localization error from 9 cm, as reported in the literature analysis of references 13, 33, and 34, to 2.72 cm, a significant improvement.

Hybrid DV-Hop, a new algorithm for anchor node localization that incorporates RSSI data, was suggested in this study. No additional hardware components or sub-systems are required to implement the proposed technique because most modern wireless sensor nodes provide RSSI values for received data packets. It is also important to note that the proposed technique has nodes that bind sensor nodes sequentially, allowing the prior sensors to serve as anchors while the remaining sensors are localized. The proposed approach was much more efficient than the other algorithms analyzed through simulations. The proposed sequential Hybrid DV-Hop algorithm with EM-PSO enhances localization accuracy by almost 95%, 90%, and 70% compared to the basic DV-Hop.

6.0 REFERENCES

1. R. Kulkarni, G. Venayagamoorthy and M. Cheng, “Bio-inspired node localization in wireless sensor networks,” in 2009 IEEE Int. Conf. on Systems, Man and Cybernetics, vol. 22, pp. 205–210, 2009.
2. D. Lavanya and S. K. Udgata, “Swarm intelligence-based localization in wireless sensor networks,” in Int. Workshop on Multi-Disciplinary Trends in Artificial Intelligence, Berlin, Heidelberg, Springer, pp. 317–328, 2011.
3. P. Singh, B. Tripathi and N. Singh, “Node localization in wireless sensor networks,” International Journal of Computer Science and Information Technologies, vol. 2, no. 6, pp. 2568–2572, 2011.
4. Boukerche, H. Oliveira, E. Nakamura and A. Loureiro, “Localization systems for wireless sensor networks,” IEEE Wireless Communications, vol. 14, no. 6, pp. 6–12, 2006.
5. Y. Liu, Z. Yang, T. Ning and W. Hongyi, “Efficient quality-of-service (QoS) support in mobile opportunistic networks,” IEEE Transactions on Vehicular Technology, vol. 63, no. 9, pp. 4574–4584, 2014.
6. S. Chu, Z. Du and J. Pan, “Symbiotic organism search algorithm with multi-group quantum-behavior communication scheme applied in wireless sensor networks,” MDPI, vol. 10, no. 3, pp. 930–952, 2020.
7. D. Liu, S. Guo, W. Chen and F. Wang, “History based multi-node collaborative localisation in mobile wireless ad hoc networks,” International Journal of Ad Hoc and Ubiquitous Computing, vol. 30, no. 2, pp. 59–72, 2019.
8. S. Kotwal, S. Gill and K. Saini, “Development of range free three-dimensional localisation in wireless sensor networks,” International Journal of Sensor Networks, vol. 31, no. 1, pp. 52–63, 2019.

9. K. Low, H. Nguyen and H. Guo, “Optimization of sensor node locations in a wireless sensor network,” in Fourth Int. Conf. on Natural Computation, IEEE, vol. 5, pp. 286–290, 2008.
10. Y. Wang, P. Wang, J. Zhang, X. Cai, W. Li et al., “A novel DV-hop method based on coupling algorithm used for wireless sensor network localisation,” International Journal of Wireless and Mobile Computing, vol. 16, no. 2, pp. 128–137, 2019.
11. J. Graefenstein, A. Albert, P. Biber and A. Schilling, “Wireless node localization based on RSSI using a rotating antenna on a mobile robot,” in 6th Workshop on Positioning, Navigation and Communication, Hannover, Germany, IEEE, pp. 253–259, 2009.
12. R. Sumathi and R. Srinivasan, “RSS-Based location estimation in mobility assisted wireless sensor networks,” in Proc. of the 6th IEEE Int. Conf. on Intelligent Data Acquisition and Advanced Computing Systems, vol. 2, no. 3, pp. 848–852, 2011.
13. Z. Guo, Y. Guo, F. Hong, Z. Jin, Y. He et al., “Perpendicular intersection: Locating wireless sensors with mobile beacon,” IEEE Transactions on Vehicular Technology, vol. 59, no. 7, pp. 3501–3509, 2010.
14. Q. Shi, H. Huo, T. Fang and D. Li, “A 3d node localization scheme for wireless sensor networks,” IEICE Electron Exp., vol. 6, no. 3, pp. 67–72, 2009.
15. L. Wang, J. Zhang and D. Cao, “A new 3-dimensional dv-hop localization algorithm,” Journal of Computing Information Systems, vol. 8, no. 6, pp. 2463–75, 2012.
16. Y. Xu, Y. Zhuang and J. Gu, “An improved 3D localization algorithm for the wireless sensor network,” International Journal of Distributed Sensor Networks, vol. 11, no. 6, pp. 1–13, 2015.
17. J. Li, X. Zhong and I. Lu, “Three-dimensional node localization algorithm for WSN based on differential RSS irregular transmission model,” Journal of Communications, vol. 9, no. 5, pp. 391–397, 2014.
18. T. Ahmad, X. Li and B. Seet, “Parametric loop division for 3D localization in wireless sensor networks,” Sensors, MDPI, vol. 17, no. 7, pp. 1697–1729, 2017.
19. Gopakumar and L. Jacob, “Localization in wireless sensor networks using particle swarm optimization,” in IET Conf. on Wireless, Mobile and Multimedia Networks, Beijing, China, pp. 227–230, 2008.
20. P. Chuang and C. Wu, “An effective pso-based node localization scheme for wireless sensor networks,” in Ninth Int. Conf.on Parallel and Distributed Computing, Applications and Technologies, Dunedin, New Zealand, IEEE, pp. 187–194, 2008.
21. J. Kennedy, “Bare bones particle swarms,” in Swarm Intelligence Sym., Indianapolis, IN, USA, IEEE, pp. 80–87, 2003.
22. R. Kulkarni and G. Venayagamoorthy, “Particle swarm optimization in wireless-sensor networks a brief survey,” IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), vol. 41, no. 2, pp. 262–267, 2011.

23. Kumar, A. Khosla, J. Saini and S. Singh, “Meta-heuristic range-based node localization algorithm for wireless sensor networks,” in Int. Conf. on Localization and GNSS, Starnberg, Germany, IEEE, pp. 1–7, 2012.
24. S. Arora and S. Singh, “Node localization in wireless sensor networks using butterfly optimization algorithm,” Arabian Journal of Science and Engineering, vol. 42, no. 8, pp. 1–11, 2017.
25. P. Singh, A. Khosla, A. Kumar and M. Khosla, “A novel approach for localization of moving target nodes in wireless sensor networks,” International Journal of Grid and Distributed Computing, vol. 10, no. 10, pp. 33–44, 2017.
26. P. Singh, A. Khosla, A. Kumar and M. Khosla, “Computational intelligence-based localization of moving target nodes using single anchor node in wireless sensor networks,” Telecommunication Systems, Springer vol. 69, no. 3, pp. 397–411, 2018.