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*Original Article*

# Analysis on Efficient Target Object Tracking in Wireless Sensor Network

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***Abstract*** - *Wireless Sensor Network (WSN) is a self-governing network with small units called sensor nodes for reading events in surrounding areas. Object tracking is the primary task in WSN applications. Target tracking is used to detect and track a target's presence constantly. Sensor nodes are used in a structured manner depending on the sensing area to be monitored for a specific application. The sensor node senses the variations in the neighboring area and transmits the data to the sink node. The data collected by sink nodes are aggregated and sent to the base station. Many researchers conducted their research on target object tracking in WSN with minimal error. But, the error rate was not reduced, and existing tracking techniques did not increase the accuracy. To address these problems, different target object tracking methods are studied.*

***Keywords*** - *Wireless Sensor Network, Target object tracking, Sensor nodes, a sink node, Neighboring area, Target tracking.*

## 1. Introduction

Wireless sensors monitor the physical process and transmit the information to the base station. Sensor nodes communicate a minimum distance through a wireless medium to accomplish a single task. Due to the development of low-powered sensor technologies, sensor nodes are employed in various applications like environmental monitoring. In wireless sensor networks, all sensor nodes have contact with the base station. WSN performed high-level information processing tasks such as detection, classification and tracking. Energy efficiency and optimized allocation of sensor nodes are essential to increase the sensor network lifetime. Target tracking in WSN is to trace the roaming path of an object.

This paper is structured as follows: Section 2 reviews the target object tracking methods in WSN. Section 3 explains the existing target object tracking methods. Section 4 explains the experimental settings with the possible comparison between them. Section 5 discusses the limitation of existing target object tracking methods. Section 6 concludes the paper.

## 2. Literature Review

New robust marine mobile Multi-Target LocAlization and Tracking termed NMTLAT scheme was introduced in [1] by removing the abnormal measurement data. The data fusion centre (DFC) employed sensor-aware and pre-processed marine data to perform target localization and trajectory tracking. But, the target object tracking accuracy was not improved by the NMTLAT scheme.

Face-based Target Tracking Technique (FTTT) was designed in [2] to minimize energy depletion and increase the sensor node lifetime. FTTT combined the prediction algorithm with face routing for detection. However, the time consumption was not reduced by FTTT.

A multi-step tracking model of Kalman filter (KF) and particle swarm optimization (PSO) was designed in [3] to identify the target trajectory and target position tracking. The multi-step KF-PSO tracking model reduced the root-mean-square error and improved the tracking efficiency. But, the computational complexity was not minimized by the multi-step tracking model. The calculation method was introduced in [4] with energy conserving objective function. The target detection probability and tracking accuracy combined energy conserved objective function. An improved lion algorithm with a Logistic chaos sequence was designed to achieve sensor management. However, the error rate was not minimized by the improved lion algorithm.

An energy-efficient and accurate network-based tracking scheme were designed in [5] for linear and non-linear target movements. The designed scheme minimized the network energy consumption with higher prediction accuracy. Though energy consumption was reduced, time consumption was not reduced using an energy-efficient and accurate network-based tracking scheme. The multi-target tracking and detection were carried out in [6] in WSN. The positioning algorithm analyzed the related targets in the target tracking algorithm. The designed algorithm used the tracked moving target's motion state between the linear and non-linear motions. But, the computational complexity was not minimized by the tracking algorithm.

A target tracking scheme was introduced in [7] to minimize power consumption. A dynamic activation range was used for waking the sensor in the target neighbourhood depending on their speed. But, the target tracking scheme did not improve the target tracking accuracy. The reliable Multi-Object Tracking Model was introduced in [8] with Deep Learning (DL) method in WMSN. The fuzzy logic method determined the cluster heads (CHs) to improve energy efficiency. RNN-T model was introduced with every sensor node to track the animals. However, a reliable multi-object tracking model did not minimize the time consumption. Sequence-to-Sequence learning (Seq2Seq) model was introduced in [9] to reduce the energy consumption for an increased lifetime of WSN. The designed framework employed DV-Hop removes the GPS dependency to locate the sensors for tracking the moving object. But, the target tracking time was not reduced by the Seq2Seq model.

An enhanced least-square algorithm depending on improved Bayesian was introduced in [10] for moving target localization and tracking. An improved Bayesian algorithm was introduced to manage the collection of sub-range probability on target predictive location with the range joint probability matrix. However, the computational complexity was not reduced by the enhanced least-square algorithm.

Consecutive Edge Node Selection (CENS) and Heuristics-base Dispensed-Advert-Oriented (HBDAO) method were introduced in [11] to identify the trusted boundary detection nodes in WSN at the same time. But, the time consumption for target tracking was not minimized by the designed method. A New robust marine mobile Multi-Target LocAlization and Tracking scheme termed NMTLAT was introduced in [12] by eliminating the abnormal measurement data from initial measurement data. But, the accuracy level was not improved by the NMTLAT scheme.

## 3. Target Object Tracking in WSN

Wireless sensor networks (WSN) are positioned in hazardous areas where it is hard to reach by humans. Energy depletion minimization and sensor network lifetime enhancement are the key demands for moving object tracking in the sensor network. Target tracking is a kind of WSN to identify the existence of the target. Sensor nodes are positioned randomly and must be monitored for particular applications like seismic vibration, humidity, temperature, pressure, wind, etc. WSN is a resource-constrained network with low-cost sensor nodes and low power sensing unit, processing unit, transceiver, and tiny battery to power up all the components. Energy depletion of nodes affected nodes' sensing operation and interrupted the target tracking process. For target tracking, the object is continuously sensed by the nodes.

### *3.1. NMTLAT*

A New robust mobile Multi-Target Localization and Tracking Scheme in marine search and rescue wireless sensor networks under Byzantine attack

A New robust marine mobile Multi-Target LocAlization and Tracking scheme termed NMTLAT was introduced by eliminating the abnormal measurement data from initial measurement data. Information entropy of the system comprised single sensor and neighbor sensors for dynamic threshold-based Byzantine node identification through mining sensor data and behavior. DFC used the sensor-aware and pre-processed marine data of beacon or honest sensors for target localization and trajectory tracking. NMTLAT comprised a new distributed and cooperative multi-target localization and tracking algorithm with the received signal strength indication (RSSI) and prior sensor location information. NMTLAT used the importance sampling method to identify the posterior probability distribution of the sensor and target location. A piecewise function was employed to classify the likelihood of drowning targets in rescue sea areas. Lyapunov's second stability theorem was employed to determine the stability of the NMTLAT.

RSSI and Maximum likelihood (ML) frames were used to address the localization and tracking issue. Levenberg– Marquardt algorithm was employed with the prior location information of beacon or honest nodes to address the ML issues. The sampling method was used to approximate the posterior distribution of the sensor and target location. When the marine target was outside the network coverage, a piecewise function was employed to classify the likelihood of identifying the target in monitoring the sea area. Lyapunov second stability theorem was employed to measure the stability of NMTLAT. The posterior Fisher Information Matrix (FIM) and Posterior Cramer–Rao Low Bound (PCRLB) were employed to evaluate the performance of our NMTLAT algorithm. The sensor nodes were moving in real-time with the actual situation of MSR-WSNs. An efficient Byzantine node identification method was used to find the Byzantine nodes in MSR-WSNs. The prior information on marine targets and beacon node location was employed to improve the robustness of localization and tracking algorithms in marine search and rescue. Information entropy and threshold-based effective Byzantine node identification method were employed by examining sensor nodes' data and behaviour. A distributed and cooperative multi-target localization and tracking algorithm were introduced to perform the mobile target's exact localization and real-time trajectory tracking.

### *3.2. Face Based Mobile Target Tracking Technique in Wireless Sensor Network*

Face-based Target Tracking Technique (FTTT) was introduced to minimize energy depletion and improve the sensor node lifetime. In addition, the designed technique helps to track the object accurately. FTTT joined the prediction algorithm with face routing for accurate detection. The sensor node in the border identified the object and chose the Triangular sensor Nodes (TN) in the face structure near the object. The process continued with triangular sensor nodes tracking the Moving Object (MO) and forecasting their next position through face routing structure. The next face-based structure employed the TN to provide continuous tracking of MO. FTTT technique was introduced depending on the face-based prediction technique for attaining uniform energy saving within all sensors. Every sensor separately and autonomously switches its standing within three stages: active, listen, or sleep. FTTT scheme forecasted the next position time of the object.

An object leaves the Region of Interest (ROI) to track the mobile object. TN sensors near the object get activated and vary their status to activate and identify the object. TN sensors transmit their wakeup message to sensor nodes expected to the next face structure target on prediction technique. FTTT utilized a less communication strategy for finding the mobile target. The outcome revealed prediction-based target tracking with an optimistic mobile tracking scheme to track the object with minimal energy. FTTT joined the collection and determination of tracking information with better implementation and minimal communication cost. The mobile object detection computed and activated the nodes before the target's arrival to minimize energy depletion.

### *3.3. Target tracking in a wireless sensor network using a multi-step KF-PSO model*

A multi-step tracking model of Kalman filter (KF) and particle swarm optimization (PSO) was introduced to determine the target trajectory and to provide target position tracking. Multi-step KF-PSO tracking model minimized the root-mean-square error and increased the tracking efficiency for diverse target trajectories. In the designed model, the network comprised populated nodes in deterministic vicinity. Every corner node was announced as the particle node. The designed system comprised target tracking through a multi-step KF-PSO combination. The multi-step tracking comprised KF and PSO to attain better tracking accuracy. KF was considered a good estimator for linear trajectory. PSO get converges in a non-linear region. In a multi-step tracking model, recursive KF gets functioned in the first step. The second step, with course approximation of KF about the target state, was supplemented in PSO to update the target position. PSO followed the target to provide a fine approximation and to move their particles closer. The tracking mechanism was twofold. KF tracked the target in the linear region. PSO provided the best estimation in the non-linear region of the target trajectory. The multi-step KF-PSO prediction model increased the expectation about the state of the target and minimized the root-mean-square error (RMSE).

## 4. Performance Analysis of Target Object Tracking Methods In WSN

Experimental evaluation of existing target object tracking methods in WSN is implemented using NS2 Simulator. The result comparison is carried out for three methods: New robust marine mobile Multi-Target LocAlization and Tracking scheme (NMTLAT), a Face-based Target Tracking Technique (FTTT) and a multi-step KF-PSO tracking model. Result analyses are carried out with existing methods with parameters are,

- Target object tracking accuracy
- Target object detection time and
- Error rate

### *4.1. Impact on Target Object Detection Time*

Target object detection time (TODT) is the amount of time consumed to detect the target object in WSN. TODT multiplies the number of target nodes and the time consumed for detecting one target sensor node. Consequently, the target object detection time is formulated as,

$$TODT = N * \text{Time consumed for predicting one target sensor node} \quad (1)$$

From (1), the target object detection time is determined. The target object detection time is determined in milliseconds (ms).

**Table 1. Tabulation for Target Object Detection Time**

| Number of Sensor Nodes (Number) | Target Object Detection Time (ms) | | |
|---|---|---|---|
| | NMTLAT Scheme | FTTT | Multi-step KF-PSO tracking model |
| 10 | 25 | 31 | 38 |
| 20 | 27 | 35 | 40 |
| 30 | 30 | 37 | 43 |
| 40 | 32 | 40 | 46 |
| 50 | 34 | 42 | 49 |
| 60 | 37 | 45 | 51 |
| 70 | 39 | 48 | 53 |
| 80 | 41 | 50 | 56 |
| 90 | 44 | 52 | 59 |
| 100 | 46 | 55 | 62 |

Table 1 describes the target object detection time for the number of sensor nodes varying from 10 to 100. Target object detection time comparison takes place on the existing New robust marine mobile Multi-Target LocAlization and Tracking scheme (NMTLAT), Face-based Target Tracking Technique (FTTT) and multi-step Kalman filter and particle swarm optimization (KF-PSO) tracking model. The graphical representation of target object detection time is illustrated in figure 1.

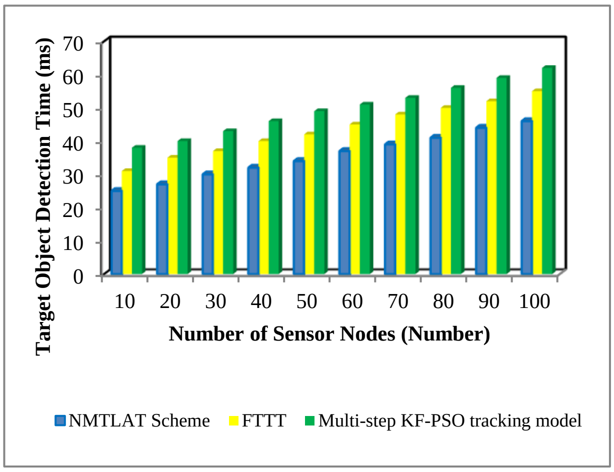


**Fig. 1 Measurement of Target Object Detection Time**

From figure 1, the target object detection time for different numbers of sensor nodes is described. The blue colour line denotes the target object detection time of the New robust marine mobile Multi-Target LocAlization and Tracking scheme (NMTLAT). The yellow and green colour lines correspondingly represent the target object detection time of FTTT and multi-step Kalman filter and particle swarm optimization (KF-PSO) tracking model. It is observed that the target object detection time using NMTLAT is lesser when compared to the FTTT and KF-PSO tracking model correspondingly. It is due to applying a piecewise function to categorize the likelihood of drowning targets in the rescue sea area. Lyapunov's second stability theorem determined the stability of the NMTLAT. Consequently, the target object detection time of NMTLAT is reduced by 19% compared to the FTTT and 29% to the KF-PSO tracking model.

### *4.2. Impact on Target Object Tracking Accuracy*

Target object tracking accuracy (TOTA) is the ratio of the number of target nodes correctly tracked to the total number of sensor nodes in WSN. It is measured in terms of percentage (%). It is formulated as,

$$TOTA = \frac{Number\ of\ target\ nodes\ that\ are\ correctly\ tracked}{Total\ number\ of\ sensor\ nodes} * 100 \qquad (2)$$

From (2), the target object tracking accuracy is calculated. The method is more efficient when the target object tracking accuracy is higher.

**Table 2. Tabulation for Target Object Tracking Accuracy**

| Number of Sensor Nodes (Number) | Target Object Tracking Accuracy (%) | | |
|---|---|---|---|
| | NMTLAT Scheme | FTTT | Multi-step KF-PSO tracking model |
| 10 | 78 | 85 | 80 |
| 20 | 81 | 88 | 82 |
| 30 | 83 | 90 | 84 |
| 40 | 85 | 92 | 87 |
| 50 | 82 | 90 | 85 |
| 60 | 80 | 88 | 84 |
| 70 | 83 | 91 | 86 |
| 80 | 86 | 94 | 89 |
| 90 | 89 | 96 | 91 |
| 100 | 91 | 97 | 93 |

Table 2 describes the target object tracking accuracy to the number of sensor nodes varying from 10 to 100. Target object tracking accuracy comparison takes place on the existing New robust marine mobile Multi-Target LocAlization and Tracking scheme (NMTLAT), Face-based Target Tracking Technique (FTTT) and multi-step Kalman filter and particle swarm optimization (KF-PSO) tracking model. The graphical representation of target object tracking accuracy is illustrated in figure 2.

Figure 2 Measurement of Target Object Detection Accuracy

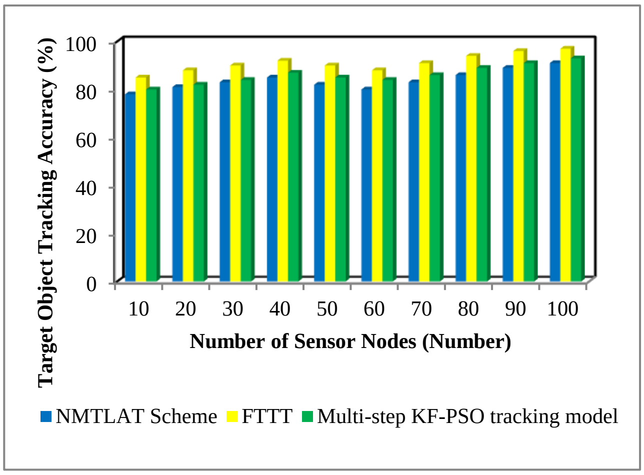


Figure 2 illustrates the target object detection accuracy for a different number of sensor nodes. The blue colour line denotes the target object detection accuracy of the New robust marine mobile Multi-Target LocAlization and Tracking scheme (NMTLAT). The yellow and green colour lines correspondingly represent the target object detection accuracy of FTTT and multi-step Kalman filter and particle swarm optimization (KF-PSO) tracking model. It is observed that the target object detection accuracy using FTTT is higher when compared to the NMTLAT and KF-PSO tracking model correspondingly. It is because the FTTT scheme forecasted the next position time of an object. An object leaves ROI to track the mobile object. FTTT joined the collection and determination of tracking information with minimal communication cost. Consequently, the target object detection accuracy of FTTT is improved by 9% compared to the NMTLAT and 6% compared to the KF-PSO tracking model.

### *4.3. Impact on Error Rate*

Error rate (ER) is the ratio of the number of target nodes incorrectly tracked to the total number of sensor nodes in WSN. It is measured in terms of percentage (%). It is calculated as,

$$ER = \frac{Number\ of\ target\ nodes\ that\ are\ incorrectly\ tracked}{Total\ number\ of\ sensor\ nodes} * 100 \qquad (3)$$

From (3), the error rate is determined. The method is said to be more efficient when the error rate is lesser.

**Table 3. Tabulation for Error Rate**

| Number of Sensor Nodes (Number) | Error Rate (%) | | |
|---|---|---|---|
| | NMTLAT Scheme | FTTT | Multi-step KF-PSO tracking model |
| 10 | 28 | 35 | 21 |
| 20 | 30 | 37 | 23 |
| 30 | 32 | 40 | 25 |
| 40 | 30 | 38 | 22 |
| 50 | 28 | 36 | 20 |

| | | | |
|---|---|---|---|
| 60 | 24 | 34 | 19 |
| 70 | 22 | 32 | 17 |
| 80 | 25 | 35 | 21 |
| 90 | 28 | 37 | 23 |
| 100 | 31 | 39 | 27 |

Table 3 describes the error rate for some sensor nodes varying from 10 to 100. Error rate comparison takes place on the existing New robust marine mobile Multi-Target LocAlization and Tracking scheme (NMTLAT), Face-based Target Tracking Technique (FTTT) and multi-step Kalman filter and particle swarm optimization (KF-PSO) tracking model. The graphical representation of the error rate is described in figure 3.

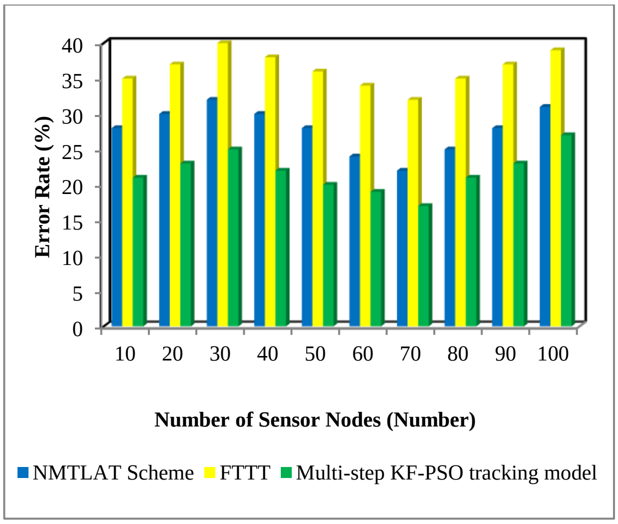


**Fig. 3 Measurement of Error Rate**

In figure 3, the error rate for the different number of sensor nodes is described. The blue line denotes the New robust marine mobile Multi-Target LocAlization and Tracking scheme (NMTLAT) error rate. The yellow and green lines correspondingly represent the error rate of FTTT and multi-step Kalman filter and particle swarm optimization (KF-PSO) tracking model. It is observed that the error rate using the KF-PSO tracking model is lesser when compared to the NMTLAT and FTTT correspondingly. This is because by applying KF and PSO to provide target position tracking. the multi-step KF-PSO tracking model reduced the root-mean-square error and improved the tracking efficiency for different target trajectories. KF tracked the target in the linear region. PSO provided the best estimation in the non-linear region of the target trajectory. Consequently, the error rate of the KF-PSO tracking model is reduced by 22% compared to the NMTLAT and 40% to the FTTT.

## 5. Discussion and Limitation on Existing Target Object Tracking Methods in WSN

NMTLAT scheme was introduced to eliminate the abnormal measurement data. The NMTLAT scheme enhanced the localization accuracy. Information entropy included single and neighbor sensors for the dynamic threshold-based Byzantine node identification method. The data fusion centre (DFC) employed sensor-aware and pre-processed marine data to perform the target localization and trajectory tracking. The NMTLAT scheme did not enhance the target object tracking accuracy.

FTTT was introduced to reduce energy depletion, increase the sensor node lifetime, and track the object precisely. FTTT joined the prediction algorithm with face routing for detection. The sensor node in the border identified object and selected Triangular sensor Nodes (TN) in the face structure near the object. The process continued with TNs tracking Moving Object (MO) and forecasting the next position through face routing structure. But, the time consumption was not minimized by the designed method.

A multi-step KF and PSO tracking model was carried out to establish the target trajectory and position tracking. The multi-step KF-PSO tracking model reduced the root-mean-square error and increased the tracking efficiency for different target trajectories. The tracking efficiency for the target trajectory was improved by the proposed method. However, the computational complexity was not decreased by the multi-step tracking model.

### *5.1. Future Direction*

Future work can be carried out using machine learning and deep learning techniques to increase target object tracking performance with improved accuracy and less time consumption.

## 6. Conclusion

A comparison of different existing target object tracking methods is illustrated. The study examined that the designed method did not minimize target object detection time consumption. The survival review shows that the multi-step tracking model did not decrease the computational complexity. In addition, the target object tracking accuracy was not enhanced by the NMTLAT scheme. The wide range of experiments on many existing target object tracking methods determines the performance with its limitations. Finally, the research can be conducted using deep learning and machine learning methods to increase the target object tracking performance.

## References

[1] Jiangfeng Xian, Huafeng Wu, Xiaojun Mei, Yuanyuan Zhang, Huixing Chen and Jun Wang, "NMTLAT: A New Robust Mobile Multi-Target Localization and Tracking Scheme in Marine Search and Rescue Wireless Sensor Networks under Byzantine Attack", *Computer Communications, Elsevier*, vol. 160, pp. 623-635, 2020.

[2] Khalid Ali, MohdFadlee A. Rasid, AduwatiSali and Borhanuddin Ali, "Face-Based Mobile Target Tracking Technique in Wireless Sensor Network", *Wireless Personal Communications, Springer*, vol. 111, pp. 1853-1870, 2020.

[3] Dhiren P. Bhagat and HimanshukumarSoni, "Target Tracking in a Wireless Sensor Network using a Multi-Step KF-PSO Model", *International Journal of Computers and Applications*, Taylors and Francis, vol. 43, no. 5, pp. 401-412, 2021.

[4] Ce Pang, Gong-guoXu, Gan-lin Shan and Yun-pu Zhang, "A New Energy Efficient Management Approach for Wireless Sensor Networks in Target Tracking", *Defence Technology*, Elsevier, vol. 17, no. 3, pp. 932-947, 2021.

[5] JayeshMunjani and Maulin Joshi, "A Non-Conventional Lightweight Auto Regressive Neural Network for Accurate and Energy Efficient Target Tracking in Wireless Sensor Network", *ISA Transactions, Elsevier*, vol. 115, pp. 12-31, 2021.

[6] XianzhenXu, Zhiyu Yuan and Yanping Wang, "Multi-Target Tracking and Detection Based on Hybrid Filter Algorithm", *IEEE Access*, vol. 8, pp. 209528 – 209536, 2020.

[7] Tauseef Ahmad and Ash Mohammad Abbas, "LeDA: Leadership Delegation Based Activation Scheme for Target Tracking in Wireless Sensor Networks", *International Journal of Information Technology, Springer,* vol. 13, pp. 541-549, 2021.

[8] Bassam A. Y. Alqaralleh, SachiNandanMohanty, Deepak Gupta, AshishKhanna, K. Shankar, and ThavavelVaiyapuri, "Reliable Multi-Object Tracking Model using Deep Learning and Energy Efficient Wireless Multimedia Sensor Networks", *IEEE Access*, vol. 8, pp. 213426 – 213436, 2020.

[9] Xiaofei Cao and Sanjay Madria, "An Efficient Moving Object Tracking Framework for WSNS using Sequence-to-Sequence Learning Model", *Peer-to-Peer Networking and Applications, Springer,* vol. 14, pp. 3915–3928, 2021.

[10] Tao Wang, Xiang Wang, Wei Shi, Zongmin Zhao, Zhenxue He and Tongsheng Xi, "Target Localization and Tracking Based on Improved Bayesian Enhanced Least-Squares Algorithm in Wireless Sensor Networks", *Computer Networks, Elsevier*, vol. 167, pp. 1-15, 2020.

[11] S. Alonshia and P. Sumathy, "Optimized Target Tracking using Heuristics Base Dispensed Advert Oriented Algorithm", *Microprocessors and Microsystems, Elsevier*, pp. 1-15, 2021.

[12] Jiangfeng Xian, Huafeng Wu, Xiaojun Mei, Yuanyuan Zhang, Huixing Chen and Jun Wang, "NMTLAT: A New Robust Mobile Multi-Target Localization and Tracking Scheme in Marine Search and Rescue Wireless Sensor Networks Under Byzantine Attack", *Computer Communications, Elsevier*, vol. 160, pp. 623-635, 2020.

[13] S. Salari, I.M. Kim, F. Chan, "Distributed Cooperative Localization for Mobilewireless Sensor Networks," *IEEE Wirel. Commun. Lett*., vol. 7, no. 1, pp. 18-21, 2018.

[14] R. Niu, A. Vempaty, P.K. Varshney, "Received-Signal-Strength-Based Localizationin Wireless Sensor Networks," *Proc. IEEE,* vol. 106, no. 7, pp. 1166–1182, 2018.

[15] B. Huang, C. Yu, B.D.O. Anderson, et al., "Estimating Distances via Connectivityin Wireless Sensor Networks," *Wirel. Commun. Mobile Comput.*, vol. 14, no. 5, pp. 541-556, 2014.

[16] S. Zaidi, A.E. Assaf, S. Affes, et al., "Accurate Range-Free Localization in Multi-Hopwireless Sensor Networks," *IEEE Trans. Commun*., vol. 64, no. 9, pp. 3886–3900, 2016.

[17] J. Cota-Ruiz, P. Rivas-Perea, E. Sifuentes, et al., "A Recursive Shortest Path Routingalgorithm with Application for Wireless Sensor Network Localization," *IEEE Sens.J.*, vol. 16, no. 11, pp. 4631–4637, 2016.

[18] Z. Wang, B. Zhang, X. Wang, et al., "Improvements of Multi-Hop Localizationalgorithm for Wireless Sensor Networks," *IEEE Syst. J.*, no. 7, pp. 1-12, 2018.

[19] O. Pandey, A. Mahajan, R.M. Hegde, "Joint Localization and Data Gathering Oversmall World WSN with Optimal Data MULE Allocation," *IEEE Trans. Veh. Technol.*, vol. 67, no. 7, pp. 6518–6531, 2018.

[20] A.E. Assaf, S. Zaidi, S. Affes, et al., "Low-Cost Localization for Multi-Hop Heterogeneous Wireless Sensor Networks," *IEEE Trans. Wireless Commun.*, vol. 15, no. 1, pp. 472–484, 2016.

[21] X. Liu, Z. Gang, X. Ma, "Target Localization and Tracking in Noisy Binary Sensornetworks with Known Spatial Topology," *Wirel. Commun. Mobile Comput.*, vol. 9, no. 8, pp. 1028–1039, 2010.

[22] H. Wang, K. Yao, D. Estrin, "Information-Theoretic Approaches For Sensor Selectionand Placement in Sensor Networks for Target Localization and Tracking, *J. Commun.Netw.*, vol. 7, no. 4, pp. 438–449, 2005.

[23] J. Feng, B. Lian, H. Zhao, "Coordinated and Adaptive Information Collecting Intarget Tracking Wireless Sensor Networks," *IEEE Sens. J.*, vol. 15, no. 6, pp. 3436–3445, 2015.

[24] S. Tomic, M. Beko, D. Rui, et al., "A Robust Bisection-Based Estimator for Toabased Target Localization in NLOS Environments," *IEEE Commun. Lett.*, vol. 21, no. 11, pp. 2488–2491, 2017.

[25] J. Lee, K. Cho, S. Lee, et al., "Distributed and Energy-Efficient Target Localizationand Tracking in Wireless Sensor Networks," *Comput. Commun.*, vol. 29, no. 13–14, pp. 2494–2505, 2006.

[26] A. Zaeemzadeh, M. Joneidi, B. Shahrasbi, et al., "Robust Target Localization Basedon Squared Range Iterative Reweighted Least Squares," in: IEEE 14th *International Conference on Mobile Ad Hoc and Sensor Systems*, pp. 380–388, 2018.