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# TARGET OBJECT TRACKING IN WSN USING SAMMON REGULARIZATION POLICY AND CIRCUMFERENCE REINFORCED PROJECTION PURSUIT AND ADAPTIVE BOOSTING

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## Abstract

In recent years, Wireless Sensor Networks (WSNs) used in extensive application ranging between military, surveillance, smart cities and so on. Target object tracking is one of the most fascinating applications in this domain of interest that specifically comprises of detecting the target object and keeps tracking of their movements. Several methods have been developed for target object tracking in WSN with minimal energy consumption. However, the accuracy level was not increased by existing tracking techniques. In order to address these problems, a novel targets object tracking method called Gaussian Distributive Sammon Regularization Policy (GG-DSRP) for efficient target object tracking in WSN is proposed. To make tracking more accurate another novel is also proposed called Circumference Reinforced Projection Pursuit and Adaptive Boosting (CRPP-AB) for tracking target object in WSN. The GG-DSRP method consists of three major processes namely reference node selection, target detection, and trajectory prediction. For this process Wilcoxon rank-sum test for identifying the reference node based on higher residual energy is applied in the first stage and in final stage, the target object trajectories are identified using Sammon projective on-policy learning algorithm to predict the target trajectories based on the state transition property. In CRPP-AB, node selection is done with Circumference Reinforced Acceleration and Adaptive Boost Target Object Classification is carried out to identify the target trajectory in WSN with Soft-Margin Support Vector Machine as the weak learners. Experimental evaluation is carried out on factors such as energy consumption and target object tracking accuracy with respect to different number of sensor nodes and data packets.

**Keywords:** WSN, target object tracking in WSN, Wilcoxon rank-sum test, Circumference Reinforced, Acceleration, Velocity, Reference Node Selection.

## INTRODUCTION

Target tracking in WSN is to detect the occurrence of a target and track it continuously. Moving target tracking is a major application of WSNs. Localization and tracking of moving targets mainly depends on energy efficiency. However, moving object tracking consumes much more energy to perform high frequency sensing and data transmission. Therefore, a great challenge is energy-efficient target tracking in WSNs. To save energy and extend the lifetime of networks while tracking a moving object effectively, this paper proposes a novel machine learning method that predicts the trajectory of the moving object.

A sequence-to-sequence learning model (Seq2Seq) was developed in [1] to predict the trajectory of a moving object and minimize the computation time. However, the accuracy of target prediction was not improved. A lightweight Auto Regressive Neural Network (ARNN) was developed in [2] for accurate and energy-efficient target tracking. However, the time consumption of target tracking was not minimized.

A novel energy-efficient management approach was developed in [3] for target tracking. However, it was not efficient to prolong its network lifetime for target tracking. A fault-tolerant sensor scheduling method was introduced in [4] for target tracking and improving the network lifetime with minimum prediction errors. However, it failed to focus on the energy harvest-tracking network.

Particle Filter with machine learning algorithm called Support Vector Machine (SVM) (PF-SVM) based energy efficient target tracking was presented in [5]. Here, support vector machine was employed in classifying with the purpose of minimizing communication cost. Also with the purpose of addressing sensor observations accessibility to each subsequent node, SVM was employed by compressing sensor observations within vicinity. Moreover, by taking closer points than the entire data points for compression ensures improvement in terms of both reliability and accuracy. However, motion features of targets were not tracked and hence there may be a probability of targets being lost in case of occlusion. To address on this aspect, a motion target tracking model employing spatiotemporal function encompassing Kalman filtering was presented in [6]. With this filtering function resulted in the removal of occlusion in tracking process. Moreover, using segmentation to detect the current target state suitable model was also deployed, therefore resulting in accuracy improvement.

In recent years, modern applications like, surveillance, trajectory object tracking and detection and locating systems have increased exponentially. Several research articles have also made an appearance utilizing several materials and methods to reach an efficient system working in real-time.

Principal component analysis and deep learning networks were combined in [7] with the purpose of designing an intelligent detection and tracking system working in real time ensuring good detection and classification accuracy. However, the time factor involved in detection and classification was not analyzed. A systematic review on object tracking and detection mechanisms using generative adversarial neural networks focusing of time was investigated in [8]. In the information society, a proportionate amount of visual information data is said to be generated in a daily basis. As far as radar research is concerned, target detection is said to be one of the crucial direction of analysis. Conventional radar target detection mechanisms are specifically designed because of constant false alarm rate (CFAR) and also several detection methods have been designed by scholars.

**Organization of the paper**

The paper includes five different sections. Section 2, discusses some related energy-efficient object tracking frameworks. In section 3, a brief discussion about the GG-DSRP and CRPP-AB method is presented. The performance results of the three methods are discussed in section 4. Finally, Section 5 provides the conclusion of the paper.

## RELATED WORKS

A three-dimensional space target tracking method was developed in [9] for minimizing the error rate of observation. But, the multiple target detection was not performed. A reliable multi-object tracking model was introduced in [10] with the deep learning approach. However, the energy efficiency was not improved in the multi-object target tracking. An enhanced least-square algorithm based on improved Bayesian was developed in [11] for tracking the targets. However, it failed to consider multi-target localization and tracking.

A hybrid filtering algorithm was designed in [12] for multi-target tracking and detection based on WSN. However, the performance of the error rate was not minimized. The multi-target localization and tracking method was introduced in [13] by eliminating abnormal measurements. But the accuracy and stability of target localization and tracking were not improved.

Ensemble methods have shown their unprecedented potentialities in enhancing the conventional machine learning techniques like, decision trees, Support Vector Machines (SVM) and so on in addressing the drawbacks involved in training imbalanced data. Ensemble learning integrates large numbers of weak classifiers with the purpose of generating machine learning technique that is found to be better than simple classifiers.

A review of object detection methods employing deep learning was investigated in [14]. In [15], the potentiality of Adaptive Boosting (AB) was combined with Convolutional Neural Network (CNN) with the purpose of designing a machine learning method, called, AB-CNN. With this type of design ensured accurate balancing of data in a timely aspect. However, the energy consumption involved in the overall process was not focused. To address on this aspect, a method called, genetic algorithm using non-dominated sorting function and extended kalman filter in generalized form was presented in [16]. With this type of design not only resulted in the improvement of energy consumption but also in the improvement of positioning prediction significantly.

## PROPOSAL METHODOLOGIES

### 3.1 GG-DSRP method

The main objective of target tracking in WSN is to locate and monitor the movement of the target continuously. The target tracking is carried out by the means of various sensor nodes deployed in the sensing environment. The deployed sensor nodes are typically small and are equipped with low-battery power. Therefore, energy management is the most significant issue in numerous applications of WSN, especially in target tracking. The higher energy consumption of the dynamic nodes reduces the network lifetime. Therefore, energy-efficient target tracking is a major challenge in WSN to enhance the lifetime of the network. Based on this motivation, a novel machine learning technique called GG-DSRP is introduced to track moving targets and saved energy to expand the lifetime of the WSN in the centralized structure.

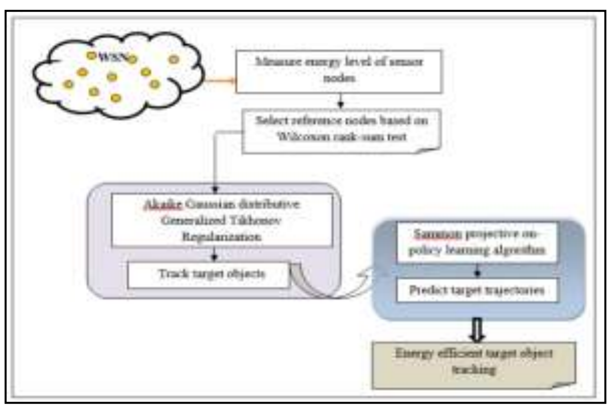


**Figure 1 Architecture Diagram of Proposed GG-DSRP method**

Figure 1 illustrates the basic architecture diagram of the proposed GG-DSRP method for target object tracking in WSN. First, the number of sensor nodes $Sn_i \in Sn_1, Sn_2 \ldots Sn_n$ are distributed in a squared network within the transmission range '$T_r$'. In the proposed technique, the energy of all the sensor nodes '$E(SN_i)$' is measured. After that, the Wilcoxon rank-sum statistic analysis is performed to identify the energy-efficient nodes called reference nodes in the network. Wilcoxon rank-sum test is a statistical test used to analyze the relationship between two statistical data (i.e. Energy of the sensor nodes and threshold value). The selected reference node sends the beacon message to the entire sensor node for identifying the target node location in the WSN.

When a target object arrived in a network, the nearby sensor node senses, monitors the target node, and transmits the information to the higher energy reference nodes. Since the lesser energy sensor nodes did not hold the information for a longer duration. The reference node receives the sensed information from the sensor node and transmits it to the base station for target tracking. After that, the base station uses the Gaussian distributive Generalized Tikhonov Regularization analysis with the sensed data to find the target object location with minimum energy consumption.

After that, the base station uses the Sammon projective on-policy learning algorithm to identify the target trajectories based on the state transition property. The on-policy learning algorithm predicts the updated state of the target object from the current state at two consecutive time intervals. After predicting the path, the Sammon projection is used for minimizing the target trajectory prediction error.

### 3.2 CRPP-AB method

The sensor scheduling problem for target object tracking refers to activating suitable reference node set from the actual node set around the predicted location of the target. To handle the problem or trade-off between tracking object quality and network lifetime, an energy efficient and network lifetime improved target object tracking method is proposed. We first adopt a Circumference Reinforced Acceleration and Velocity-based reference node selection model to organize the sensor nodes or select reference nodes activated in the tracking process. Then, to reduce the trade-off between quality and network lifetime in advance, the Statistical Projection Pursuit domain is constructed near the predicted location of the target object. Finally, with the target and reference node in target object tracking domain learn the optimal scheme by using an Adaptive Boost Target Object Classification.

## RESULTS AND DISCUSSIONS

The simulation results of the GG-DSRP and CRPP-AB technique are compared with Seq2Seq model [1] are discussed in this section with different performance metrics such as energy consumption and target tracking accuracy with respect to a number of sensor nodes. The performance of proposed and existing methods is discussed with help of a table and graph.

### 4.1 Impact of energy consumption

Energy is the most significant metric to enhance the lifetime of the network. The minimum energy consumption of the sensor node enhances the network lifetime and performs accurate target tracking. Energy consumption is referred to as the amount of energy consumed by the sensor nodes to perform the target tracking in the network. The formula for calculating the energy consumption is given below,

$$\mathrm{Conp_E} = \mathrm{n} * \mathrm{E_c}\ (\mathrm{SSn})$$

Where, $\mathrm{Conp_E}$ indicates energy consumption, n denotes the number of sensor nodes, $\mathrm{E_c}$ indicates energy consumed by the single sensor nodes $(\mathrm{SSn})$. The performance of energy consumption is measured in terms of a joule (J).

**Table 1 Comparison of Energy consumption**

| Number of sensor nodes | Energy consumption (joule) | | |
|---|---|---|---|
| | Seq2Seq model | GG-DSRP | CRPP-AB |
| 50 | 24 | 21.5 | 17.5 |
| 100 | 27 | 24 | 19.35 |
| 150 | 34.5 | 28.5 | 21 |
| 200 | 36 | 32 | 23.35 |
| 250 | 40 | 37.5 | 25 |
| 300 | 45 | 42 | 28.25 |

Table 1 reports the performance assessment results of energy consumption with a number of sensor nodes using Seq2Seq model [1], GG-DSRP and CRPP-AB method. For the simulation purposes, the number of sensor nodes is taken in the ranges from 50 to 300. For each method, six different results are observed with respect to the number of sensor nodes. The observed results indicate that the performance of energy consumption using the GG-DSRP and CRPP-AB methods is considerably minimized when compared to existing method. The simulation results are plotted in the graph.

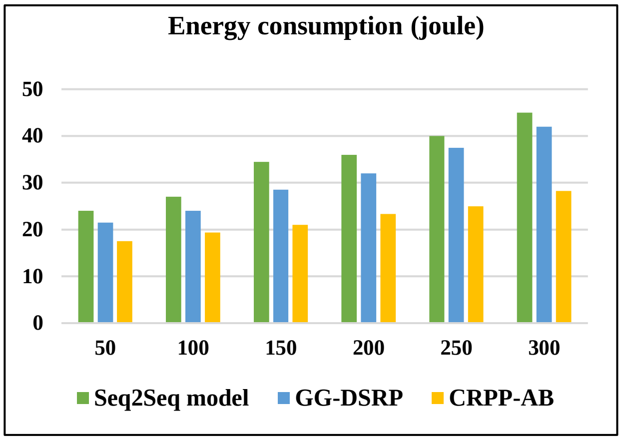


**Figure 2 Graphical representation of energy consumption**

Figure 2 reveals the performance analysis of energy consumption against a number of sensor nodes using Seq2Seq model [1], GG-DSRP and CRPP-AB method. As shown in figure 2, the energy consumption of all three methods is increased while increasing the number of sensor nodes. However, comparatively, the GG-DSRP and CRPP-AB method decreases the energy consumption when compared to existing method.

**4.2 Impact of Target tracking accuracy:**

The accuracy of target tracking is calculated based on the number of (No. of) sensor nodes that correctly transmit the target object information to the base station. Therefore, the accuracy is mathematically calculated as given below,

$$\mathrm{Tar\_Trac}_{\mathrm{Acc}} = \left(\frac{\text{No. of Sns correctly transmits the information}}{\mathrm{n}}\right) * 100$$

Where, $\mathrm{Tar\_Trac}_{\mathrm{Acc}}$ denotes target tracking accuracy, n denotes the number of sensor nodes. It is measured in terms of percentage (%).

**Table 2 Comparison of target tracking accuracy**

| Number of sensor nodes | Target Tracking Accuracy (%) | | |
|---|---|---|---|
| | Seq2Seq model | GG-DSRP | CRPP-AB |
| **50** | 90 | 94 | 96 |
| **100** | 89 | 93 | 95.35 |
| **150** | 88.66 | 92.66 | 95.15 |
| **200** | 88.5 | 92.5 | 94.35 |
| **250** | 88 | 92.4 | 94 |
| **300** | 87.66 | 92 | 93.75 |

Table 2 reports the simulation results of the target tracking accuracy versus the number of sensor nodes. The number of sensor nodes considered for simulation varied from 50,100 …300. The table value indicates the performance results of target tracking accuracy using Seq2Seq model [1], GG-DSRP and CRPP-AB method. Among the three methods, the GG-DSRP and CRPP-AB outperforms well in terms of achieving higher accuracy. The overall results indicate that the performance of the target tracking accuracy of the GG-DSRP and CRPP-AB are considerably increased when compared with existing [1] method.

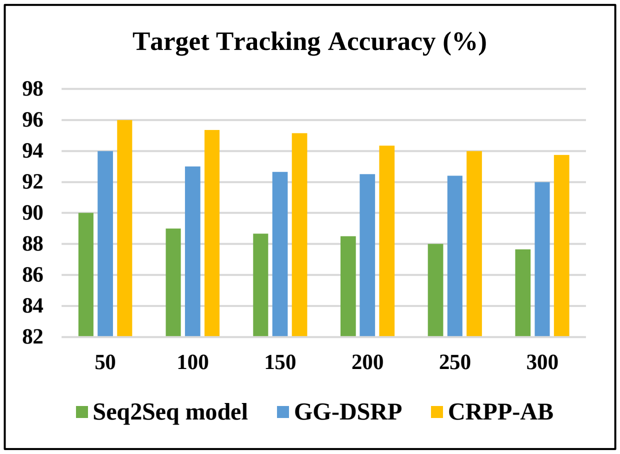


**Figure 3 Graphical representation of Target tracking accuracy**

The above figure 3 illustrates the performance of target tracking accuracy with respect to a number of sensor nodes. As shown in the graph, the performance of the tracking accuracy is observed at the y-axis and the number of sensor nodes on the x-axis. The graphical results indicate that the performance of the GG-DSRP and CRPP-AB provides improved performance over the existing method [1].

## CONCLUSION

Tracking target objects provide a lot of challenges in WSNs. In this paper, a novel GG-DSRP and CRPP-AB methods are developed for accurately tracking a target with minimum time. First, the energy-efficient sensor nodes are identified for increasing the network lifetime. In this way, energy-efficient target tracking is performed in WSN. We observed that the proposed methods performs better than the existing method in terms of the energy consumption and target tracking accuracy. The results presented in the paper are for a network where sensors are distributed in a region randomly and the density of sensors is assumed uniform. The discussed results have revealed that the CRPP-AB technique has considerably improved the target tracking accuracy with minimum time as well as error rate than the existing method [1] and GG-DSRP Method.

## REFERENCES

[1] 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, Volume 14, 2021, Pages 3915–3928. https://doi.org /10.1007/s12083-021-01157-8
[2] Jayesh Munjani 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, Volume 115, September 2021, Pages 12-31. https://doi.org/10.1016/j.isatra. 2021.01.021
[3] Ce Pang, Gong-Guo Xu, Gan-lin Shan, Yun-Pu Zhang, "A new energy-efficient management approach for wireless sensor networks in target tracking", Defence Technology, Elsevier, Volume 17, Issue 3, 2021, Pages 932-947. https://doi.org/10.1016/j.dt.2020.05.022
[4] Zhiyi Qu, Huihui Xu, Xue Zhao, Hongying Tang, Jiang Wang, Baoqing Li, "A fault-tolerant sensor scheduling approach for target tracking in wireless sensor networks", Alexandria Engineering Journal, Elsevier, Volume 61, 2022, Pages 13001–13010. https://doi.org/10.1016/j.aej.2022.07.008

[5] K. Reddy Madhavi, Mohd Nasrun Mohd Nawi, B. Bhaskar Reddy, K. Baboji, Kakarla Hari Kishore, S.V. Manikanthan, "Energy efficient target tracking in wireless sensor network using PF-SVM (particle filter-support vector machine) technique", Measurement: Sensors, Elsevier, Jan 2023 [particle filter-support vector machine (PF-SVM)]
[6] Jie Wang, Shibin Xuan, Hao Zhang, Xuyang Qin, "The moving target tracking and segmentation method based on space-time fusion", Multimedia Tools and Applications, Springer, Sep 2022
[7] Nuha H. Abdulghafoor, Hadeel N. Abdullah, "A novel real-time multiple objects detection and tracking framework for different challenges", Alexandria Engineering Journal, Elsevier, Mar 2022
[8] Saeed Matar Al Jaberi, Asma Patel, Ahmed N. AL-Masri, "Object tracking and detection techniques under GANN threats: A systemic review", Applied Soft Computing, Elsevier, Mar 2023.
[9] Thulio G. S. Amorim, Leonardo A. Souto, Tiago P. Do Nascimento, Martin Saska, "Multi-Robot Sensor Fusion Target Tracking With Observation Constraints", IEEE Access, Volume 9, 2021, Pages 52557 – 52568. DOI: 10.1109/ACCESS.2021.3070180
[10] Bassam A. Y. Alqaralleh, Sachi Nandan Mohanty, Deepak Gupta, Ashish Khanna, K. Shankar, and Thavavel Vaiyapuri, "Reliable Multi-Object Tracking Model Using Deep Learning and Energy Efficient Wireless Multimedia Sensor Networks", IEEE Access, Volume 8, Pages 213426 – 213436. DOI: 10.1109/ACCESS.2020.3039695
[11] 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, Volume 167, 2020, Pages 1-15, https://doi.org/10.1016/j.comnet.2019.106968
[12] Xianzhen Xu, Zhiyu Yuan, and Yanping Wang, "Multi-Target Tracking and Detection Based on Hybrid Filter Algorithm", IEEE Access, Volume 8, September 2020, Pages 209528 – 209536. DOI: 10.1109/ACCESS.2020.3024928
[13] 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, Volume 160, 2020, Pages 623-6, Pages 35. https://doi.org/10.1016/j.comcom.2020.06.034
[14] Nkalubo Lenard Byenkya, Nakibuule Rose, "A Review on Real-Time Object Detection Models using Deep Neural Networks", International Conference on Information systems and Emerging Technologies, Oct 2022
[15] Aboozar Taherkhani, Georgina Cosma, T.M McGinnity, "AB-CNN: An Adaptive Boosting algorithm for Convolutional Neural Networks to classify Multi-Class Imbalanced datasets using Transfer Learning", Neurocomputing, Elsevier, Mar 2020
[16] Ehsan FayaziBarjini, Davood Gharavian, Mohammadbagher Shahgholian, "Target tracking in wireless sensor networks using NGEKF algorithm", Journal of Ambient Intelligence and Humanized Computing, Springer, Oct 2019.