International Journal of Control and Automation
Vol. 13, No. 2s, (2020), pp. 312-329

Weighted Majority X-Means Ensemble Cluster Based Quadratic Discriminant Analysis for Resource Efficient Target Object Detection in WSN Using IOT

T.S.Prabhu[1], Dr.V.Jaiganesh[2]
[1]Research Scholar, Computer Science, Dr.N.G.P. Arts and Science College.
Email: prabhu.s@kgcas.com
[2]Professor, PG & Research in Computer Science, Dr.N.G.P. Arts and Science College

Abstract

Energy efficiency is a considerable problem to be resolved during the process of target object detection in WSN because it determines the lifetime of the sensor network. Several research works are developed for target object detection in wireless network using different techniques. But, the object detection accuracy of existing techniques was poor. Besides, the amount of energy utilization was more. In order to overcome such limitations, Weighted Majority X-means Ensemble Clustering based Quadratic Discriminant Analysis (WMXEC-QDA) technique is proposed. Initially, the WMXEC technique considers numbers of sensor nodes that are arbitrarily positioned in wireless network and which are communicated using IoT. After that, WMXEC-QDA technique applies X-means Ensemble Clustering (XEC) algorithm where it generates 'n' number of weakX-means cluster result for each input sensor node in network. Then, XEC algorithm applies weights for each weak X-means cluster result. Subsequently, WMXEC-QDA technique designs a strong cluster by considering majority weights of all weak X-means cluster results with lower false positive rate. Finally, designed strong cluster in WMXEC-QDA technique groups each sensor node into consequent clusters with minimal amount of time complexity. Followed by, the WMXEC-QDA technique determines sensor node with higher residual energy as cluster head in order to effectively gather data about the target objects. After data gathering, cluster head forwards it to the sink node by means of the nearest cluster head. Then, sink node transmits the sensed data to the base station where it applies Quadratic Discriminant Analysis to preciselydetermine the target objects within the network. This assists for WMXEC-QDA technique to enhance the accuracy of target objects detection in WSN with lower time. The WMXEC-QDA technique conducts simulation work using metrics such as object detection accuracy, object detection time, false positive rate and energy usage with respect to a number of sensor nodes..

Keywords: *Ensemble, IoT, Quadratic Discriminant Analysis, Sensor nodes, Strong Cluster, Target Objects, WSN, X-means clustering*

1. Introduction

Target objects detection is a one of the significant process in WSN where energy efficiency is a concern. There are different methods were designed in existing works to address this issue. However, resource efficient target object detection was not achieved. Therefore, a novel technique called WMXEC-QDA is designed in this research work by using X-means Ensemble Clustering and Quadratic Discriminant Analysis.

Multi-hop decision gathering scheme was developed in [1] for enhancing accuracy of target-detection in WSNs. However, the amount of time taken for target-detection was very higher. Particle Swarm Optimization based Energy Efficient Target Tracking (P-EETT) was performed in [2]. But, accuracy of object detection was poor.

Moving target tracking through distributed clustering (MTDC) mechanism was presented in [3] with aim of increasing the accuracy via efficient aggregation of sensing

ISSN: 2005-4297 IJCA

data from member nodes. However, false positive rate of target detection was more. Massive multiple-input multiple-output (MIMO) system was introduced in [4] for accomplishing target discovery process in a cluster-based WSN with minimal amount of time. But, energy consumption during the target detection was higher.

A novel Statistic Experience-based Adaptive One-shot Network (SENet) was developed in[5] to resolve the object detection problem and there by enhancing the real-time performance. However, object detection time was not reduced. Hybrid cluster-based target tracking (HCTT) was performed in [6]to get better network scalability and energy efficiency in WSN. But, the object detection accuracy using HCTT was not adequate.

A prediction-based clustering algorithm was carried out in [7] for minimizing the message overhead during the object discovery process. However, energy effective target discovery was not obtained. A Dynamic Clustering Algorithm was employed in [8] for increasing energy efficiency of target prediction in WSN.But, the object detection performance was poor.

An energy-efficient tracking cluster structure was designed in [9] with objective of solving the issue of node energy consumption in WSN. However, time complexity involved during the energy-efficient tracking was very higher. A game theory approach was introduced in [10] to enhance target tracking performance in sensor networks. But, the amount of time required for detecting the target objects was more.

In order to resolve the above said conventional problems, WMXEC-QDA technique is designed in this research work. The main contributions of WMXEC-QDA technique is described in below,

To improve the performance of resource efficient target object detection in WSN when compared to state-of-the-art works, WMXEC-QDA technique is proposed with help ofX-means Ensemble Clustering (XEC) algorithm and Quadratic Discriminant Analysis Based Target Object Detection (QDA-TOD) Algorithm.

To efficiently carry out data aggregation process with minimal amount of energy consumption in WSNwhen compared to conventional works, XEC algorithm is designed in WMXEC-QDA technique. XEC algorithm construct a strong cluster for grouping the sensor nodes in the network based on their residual energy level.

To minimize the false postive rate of target objects detections in WSN when compared to traditional works, QDA-TOD Algorithm is applied in WMXEC-QDA technique. Because, Quadratic discriminant analysis employed inWMXEC-QDA technique is a variation of LDA that performs non-linear separation of data to improve the classification accuracy of target object discovery.

The residual structure of the paper is constructed as follows: In Section 2, WMXEC-QDA technique is described with the assist of architecture diagram. In Section 3, Simulation settings are shown and the performance results areexplained in Section 4. Section 5 presents the literature survey. Section 6 portrays the conclusion of the paper..

2. WEIGHTED MAJORITY X-MEANS ENSEMBLE CLUSTERING BASED QUADRATIC DISCRIMINANT ANALYSIS TECHNIQUE

The Weighted Majority X-means Ensemble Clustering based Quadratic Discriminant Analysis (WMXEC-QDA) technique is designed in order toachieve higher accuracy for target object detection in WSN. The WMXEC-QDAtechnique is a machine learning technique in which multiple cluster results are combined to produce strong clustering result. In WMXEC-QDA technique, input sensor nodes are clustered according to on the majority weightsdetermined by the ensemble. Therefore, WMXEC-QDA techniqueeffectively performs node clustering process in WSN with higher accuracy andlower time. The architecture diagram of WMXEC-QDA technique is shown in below Figure 1.

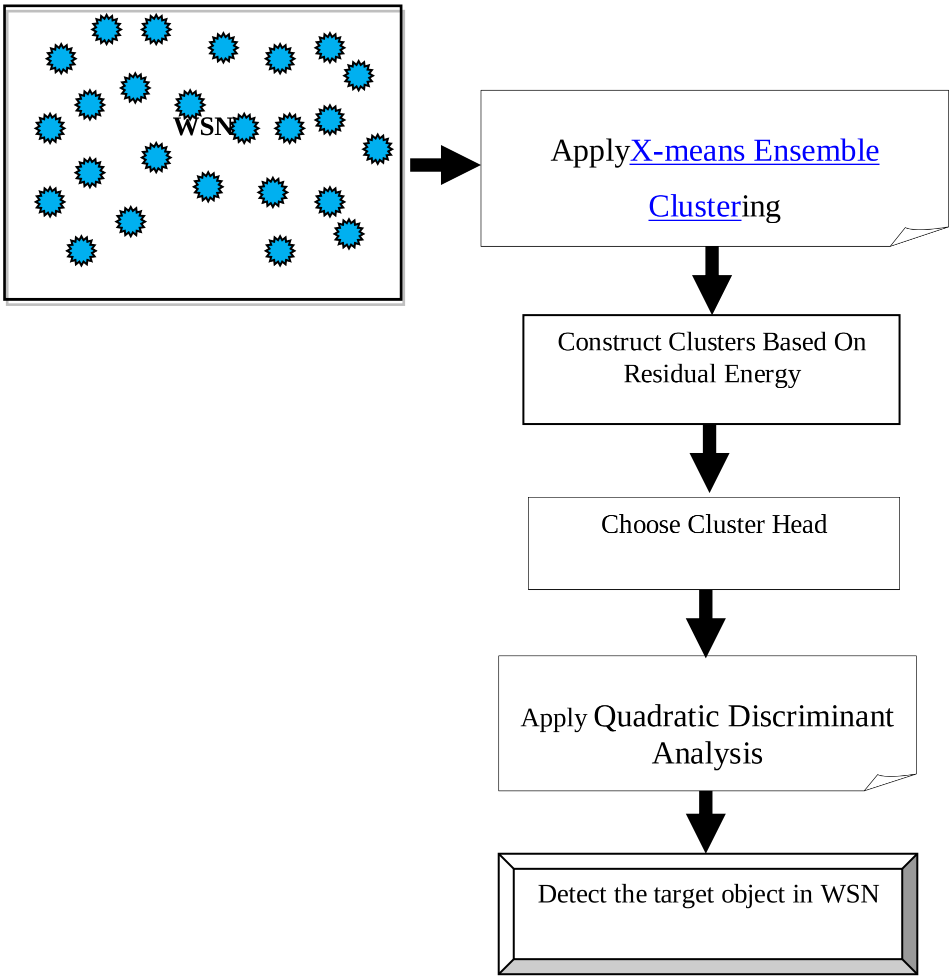

Figure 1 WMXEC-QDA technique for Target Object Detection in WSN

Figure 1 depicts the flow processes of the WMXEC-QDA techniquefor accurate target objects detection in WSN. As presented in above figure, sensor nodes are randomly considered in the sensing area. Next, the X-means Ensemble Clustering is applied in WMXEC-QDA technique with objective of grouping the sensor nodes depends on their residual energy level. Afterward, WMXEC-QDA technique finds cluster head to collects the sensed data regarding target objects and thensent these data to the base station via a sink node. At the base station, WMXEC-QDA technique applies Quadratic Discriminant Analysis in order todiscover the target objects in WSN with enhanced accuracy and minimal time. The extensive process of WMXEC-QDA technique is shown in the following subsection.

1. X-means Ensemble Clustering Algorithm

X-means Ensemble Clustering (XEC) algorithm is designed in WMXEC-QDA technique to increase data aggregation performance in WSN by efficiently forming nodeclusters. The XEC algorithm considers X-means cluster as weak learner.

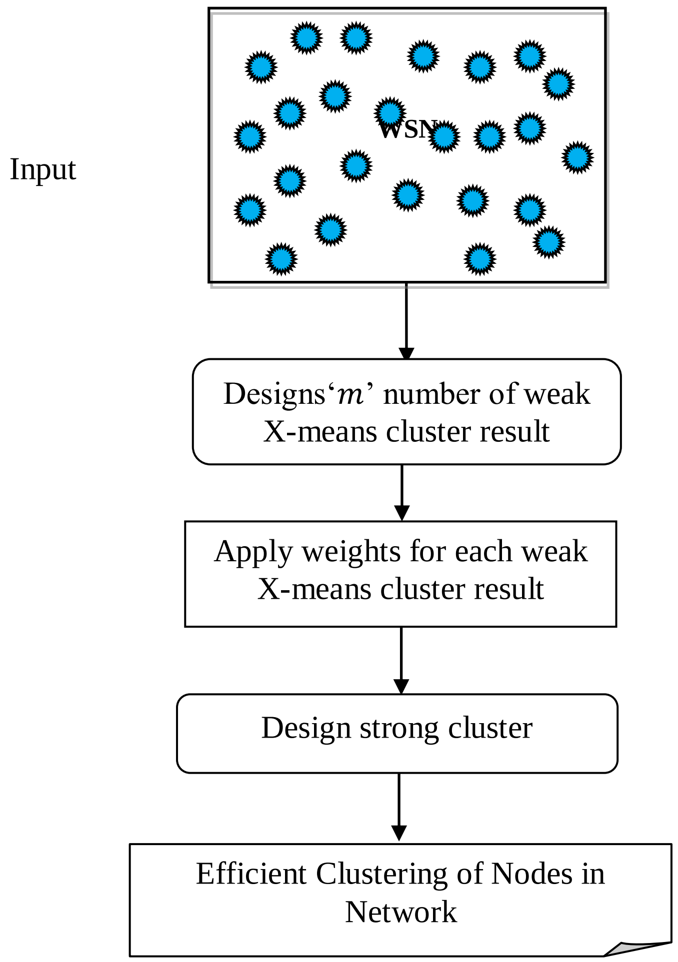

Figure 2 Block Diagram of XEC algorithm

Figure 2 presents the overall processes of XEC algorithm. As demonstrated in the above diagram, XEC algorithm initially considers a number of sensor nodes in WSN which are represented as '$s_1, s_2, s_3, .., s_n$'. Here, 'n' denotes a total number of sensor nodes. Next, XEC algorithm obtains 'm' number of weak X-means cluster results for each sensor node. During the weak X-means clustering process,residual energy of sensor node is determined using below,

$$\alpha_{\varepsilon\,(s)} = \varepsilon_I - \varepsilon_c (1)$$

From the above mathematical formula (1), '$\alpha_{\varepsilon\,(S)}$' denotes the residual energy of node in wireless network. Here, 'ε_I' refers the initial energy of the sensor nodes whereas 'ε_c' point outs the amount of energy consumed by the node for gathering data in a network. By using the above mathematical expression (1), weak X-means clusterestimates residual energy for each sensor node. The weak X-means cluster process begins with arbitraryinitialization of number of clusters 'x' and centroids 'k'. Subsequently, weak X-means clustercalculates the similarity between each sensor node and centroids by considering their residual energy level.

The weak X-means clusterutilized dice correlation coefficient measurement for constructing efficient node clusters. From that,similarities between eachsensor nodes 's_i' and cluster centroid 'k_j' is determined as follows,

$$sim\ (s_i, k_j) = \frac{s_i \cap k_j}{|s_i| * |k_j|} \quad (2)$$

From the above mathematical equation (2), '$\cap$' symbolizes a mutual dependence between sensor node 's_i' and cluster centroid 'k_j' whereas '$|s_i|$'and '$|k_j|$' represents the cardinalities between the sensor node 'd_i' and cluster centroid 'k_j'. The dice correlation coefficient '$sim\ (s_i, k_j)$' value is always ranges between the '0' and '1'. If '$sim\ (s_i, k_j) = 1$', then the sensor node is grouped into corresponding cluster centroid. When '$sim\ (s_i, k_j) = 0$', the sensor node is dissimilar to cluster centroid. Then,Weak X-means clusteremployedBayesian information criterion in order to get betternode clustering performance in wireless network.

In weak X-means cluster, the Bayesian information criterion chooses most appropriate sensor node for an each cluster centroids. Thus, the objective of Bayesian information criterion is to group the sensor node which has maximum dice correlation value to particular centroid using below formula,

$$X\_Means\ Cluster = arg \max_{c} \sum_{j=1}^{x} \sum_{d_i \in c_i} sim(s_i, k_j) \quad (3)$$

From the mathematical representation (3), 'c_i'denotes the set of sensor nodes that belong to cluster 'j'. From that,weak X-means clustergroups eachsensor nodesto the cluster whose dice correlation value from the cluster centroid is higher of all the cluster centroid by using Bayesian information criterion. Next, cluster centroid is updated by considering the weighted average of dice correlation value of allsensor nodes in that cluster. Let us assume '$s_1, s_2, .., s_n$' be number of sensor nodes within cluster 'c_i'. Accordingly, re-determination of new cluster centroid 'k_i^*' is mathematically performed as,

$$k_i^* = \frac{\sum_{s_i=1}^{n} sim(s_i, k_j)}{n} \quad (4)$$

From the above mathematical equation (4), s_i indicates the number of sensor nodes in i^{th} cluster. This re-estimation of cluster centroids in weak X-means clustergives better clustering results for efficiently perform data collection process in WSN. This process ofweak X-means cluster is recurrent until there is no variation in cluster centroids. The node clustering accuracy of weak X-means clusteris not sufficient to get better target objection detection performance. Therefore, an ensemble method called weighted majority algorithm is applied in XEC algorithm in order to further boost the clustering performance of weak X-means cluster. With the help of anensemble method, XEC algorithm generates 'm' number of weak X-means cluster results for each sensor node in WSNusing below,

$$\beta(s_i) = \beta_1(s_i) + \beta_2(s_i) + \cdots + \beta_m(s_i) \qquad (5)$$

Consequently, XEC algorithm apply weight 'ω_i' for each weak X-means clusterresults '$\beta(s_i)$' using below,

$$\omega_i \rightarrow \sum_{i=1}^{m} \beta(s_i) \qquad (6)$$

Thus, the majorityweight of all weak X-means clusterresults are combined in XEC algorithm to create a strong cluster that accurately grouping the sensor nodes in the WSN depends on their residual energy. From that, strong cluster output is mathematically obtained using below,

$$\gamma\,(s_i) = arg\max_{m} \omega(\beta(s_i)) \qquad (7)$$

From the above equation (7), '$\gamma(s_i)$' signifies the final strong cluster result in order to significantly group the sensor nodes based on residual energy. Here, '$arg\max_{m} \omega$' refers majority weights of weak X-means clusteroutput. By designing a strong cluster, proposed XEC algorithm accurately group all the sensor nodes in WSN based on their residual energy level with minimal amount of time.

The algorithmic steps of XEC is explained in below,

```
// X-means Ensemble Clustering Algorithm
Input: Number Of Sensor Nodes 's1, s2, s3, ..... sn'
Output: Effective clustering of nodes for data aggregation
Step 1:  Begin
Step 2:    For each number of input sensor nodes 'sn' in wireless network
Step 3:             Determine the residual energy level using (1)
Step 4:             Generate 'm' number ofweak X-means cluster results
Step 5:             Apply a weights for each weak X-means cluster resultusing (6)
Step 6:             Designstrong cluster result using majority weights using (7)
Step 7:            Strong clusteraccurately groups sensor nodes into a corresponding
cluster
Step 8:        End For
Step 9:   For each cluster in network
Step 10:       Select cluster head
Step 11:    End For
Step 12:      Cluster head collects data about target objects from its members
Step 13:       Cluster head forwards sensed data to sink node
Step 14:       Sink node receive gathered data and sent it to the base station
Step 15:End
```

Algorithm 1 X-means Ensemble Clustering

Algorithm 1 presents the step by step processes of XEC to enhance the accuracy of target object detection. As depicted in the above algorithmic steps, XEC algorithm at the startacquires a number of sensor nodes as input and then,XEC algorithm gets 'm' number of weak X-means cluster results. Afterward, XEC algorithm assignsweights for each weak X-means cluster result. Next, XEC algorithm build strong cluster by using majority weights of weak mean shift cluster results.After that,developed strong cluster in XEC algorithm exactly groups the sensor nodes into dissimilar clusters based on measured residual energy. For each cluster, thenXEC algorithm identifies a sensor node with higher residual energy as a cluster head.Thiscluster head collects the dataof target objectsthat entered into a network from its cluster member. Followed by, cluster head broadcasts gathered data to base station via a sink node for predicting the target objects in WSN.

2.2 Quadratic Discriminant Analysis based Target Object Detection

Quadratic Discriminant Analysis Based Target Object Detection (QDA-TOD) Algorithm is proposed in WMXEC-QDA technique with aim of enhancing the performance of target object detection in WSN with higher accuracy and minimal time by usingcollected data. QDA-TOD Algorithm is employed to separate measurements of two or more classes (i.e. target object or not) with help of a quadric surface. In QDA-DSL Algorithm, the class label 'z' is assumed to be quadratic in the measurements of observations 'X' using below,

$$X^T AX + b^T X + c \tag{8}$$

The Quadratic Discriminant Analysis is derived from probabilistic models which model the class conditional distribution of the data ($P(X/z = k)$ for each class. The target object is predicted by using Bayes' rule which as follows,

$$P(z = k/X) = \frac{P(X/z=k)P(z=k)}{P(X)} \tag{9}$$

$$P(z = k/X) = \frac{P(X/z=k)P(z=k)}{\sum_1 P(X/z=1)P(z=1)} \tag{10}$$

From the above mathematical expressions (9) and (10), QDA-TOD Algorithm selects the class which maximizes this conditional probability. The quadratic discriminant analysis $P(X/z)$ is modelled as a multivariate Gaussian distribution with density using below expression,

$$P(X/z = k) = \frac{1}{(2\pi)^s |\sum_k|^{\frac{1}{2}}} \exp(-\frac{1}{2}(X - \mu_k)^t \textstyle\sum_k^{-1})(X - \mu_k) \tag{11}$$

From the above mathematical formula (11), 's' denotes the number of sensor nodes and 'μ_k'indicates the class means. By using the above mathematical equations, QDA-TOD Algorithm finds outs target objects in WSN with a minimal amount of time complexity. The algorithmic processes of QDA-TOD Algorithm is explained in below,

// Quadratic Discriminant Analysis Based Target Object Detection Algorithm
Input: Number Of Sensor Nodes '$\{s_1, s_2, \ldots, s_n\}$'; collected data about target nodes
Output: Achieve higher objects detection accuracy
Step 1:Begin

Step 2: For each collected data
Step 3: ApplyQuadratic Discriminant Analysis using (8)
Step 4: Measuremultivariate Gaussian distribution using (9)
Step 5: ApplyBayes' rule using (10) and (11)
Step 6: Accurately find target objects in WSN
Step 7: End For
Step 8:End

Algorithm 2 Quadratic Discriminant Analysis Based Target Object Detection

Algorithm 2 presents the step by step processes of QDA-TOD. With the support of above algorithmic steps, QDA-TOD algorithms exactly discover the target objects in wireless sensor by using the collected data. From that, QDA-TOD algorithm gets betteraccuracy for target object detection with minimal amount of time when compared to conventional works.

3. SIMULATION SETTINGS

Toestimate the performance of proposed, WMXEC-QDA technique is implemented in NS2.34 Simulator. The WMXEC-QDA technique considers 500 senor nodes in sensing network area of 1200 m * 1200 m. The simulation parameters are shown in Table 1.

Table 1 Simulation Parameters

Simulation Parameters	Values
Network Simulator	NS2.34
Square area	1200 m * 1200 m
Number of sensor nodes	500
Mobility model	Random Waypoint model
Speed of sensor nodes	0 – 20 m/s
Simulation time	250sec
Protocol	DSR
Number of runs	10

The effectiveness of WMXEC-QDA technique is determined in terms of object detection accuracy, object detection time and false positive rate and energy usage. The simulation result of WMXEC-QDA technique is compared against traditionalMulti-hop decision gathering scheme [1] and Particle Swarm Optimization based Energy Efficient Target Tracking (P-EETT) [2].

4. PERFORMANCE ANALYSIS

In this section, the experimental result of WMXEC-QDA technique is discussed. The performance of WMXEC-QDA technique is compared against existing Multi-hop decision gathering scheme [1] and Particle Swarm Optimization based Energy Efficient Target Tracking (P-EETT) [2] respectively. The performance of WMXEC-QDA technique is analyzed along with the following metrics with the help of tables and graphs.

ISSN: 2005-4297 IJCA

4.1 Simulation Measure of Object Detection Accuracy

In WMXEC-QDA technique, Object detection accuracy 'ODA' estimate how the base station exactlydetects the target objects in WSN based oncollected data. Thus, object detection accuracy determined as the ratio of the number of sensor nodes correctly provide the data about the target objects to the total number of sensor nodes. Theobject detection accuracy is mathematically obtained as follows,

$$ODA = \frac{K_{CPD}}{n} * 100 \quad (12)$$

From the above mathematicalequation (12), 'K_{CPD}' denotes a number of sensor nodes accurately provide the gathered data regarding the target objects whereas 'n' symbolizes a total number of sensor nodes in a network. The object detection accuracy is evaluated in terms of percentage (%).

Sample calculation for Object Detection Accuracy:

- ✓ **ProposedWMXEC-QDA technique:** Total numbers of sensor nodes are 50 and the number of sensor nodes preciselyprovide the collected data is 48. Then object detection accuracy is acquired as follows,

$$ODA = \frac{48}{50} * 100 = 96\ \%$$

- ✓ **Existing Multi-hop decision gathering scheme:**numbers of sensor nodes are 50 and the numbers of sensor nodes exactlyprovide the collected data is 42. The object detection accuracy is computed as follows,

$$ODA = \frac{42}{50} * 100 = 84\ \%$$

- ✓ **Existing P-EETT:**numbers of sensor nodes are 50 and the numbers of sensor nodes properly provide the collected data is 37. The object detection accuracy is calculated as follows,

$$ODA = \frac{37}{50} * 100 = 74\ \%$$

The comparative result of object detection accuracy based on diverse number of sensor nodes in the range of 50-500 using three methods namely WMXEC-QDA technique and existing Multi-hop decision gathering scheme [1] and P-EETT [2] is presented in below Table 1. When conducting experimental evaluationusing100 sensor nodes, proposed WMXEC-QDA technique attains 97 % object detection accuracy whereas conventional Multi-hop decision gathering scheme [1] and P-EETT [2] gets 85 % and 76 % respectively. Thus, it is descriptive that the object detection accuracy in WSN using proposed WMXEC-QDA technique is very higher when compared to other conventional works.

Table 2 Tabulation Result of Object Detection Accuracy

Number of sensor nodes	Object Detection Accuracy (%)		
	WMXEC-QDA technique	Multi-hop decision	P-EETT

		gathering scheme	
50	96	84	74
100	97	85	76
150	95	87	79
200	93	85	80
250	91	86	81
300	93	86	80
350	91	85	83
400	92	83	81
450	90	82	79
500	93	82	78

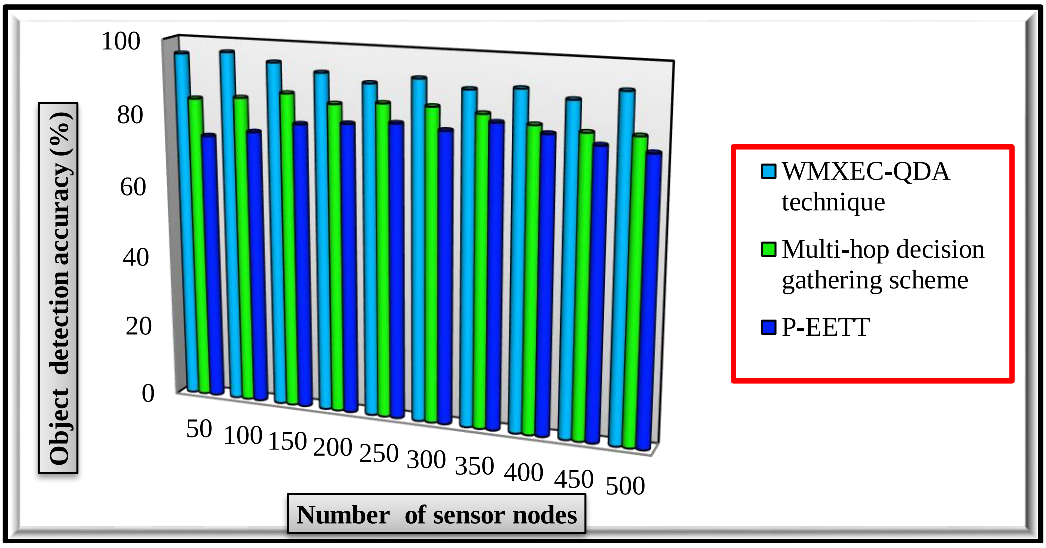

Figure 3 Graphical Result of Object Detection Accuracy versus Number of Sensor Nodes

Figure 3 depicts the graphical result of object detection accuracy along with a diverse number of sensor nodes for three methods namely WMXEC-QDA technique, Multi-hop decision gathering scheme [1] and P-EETT [2]. As demonstrated in the above graphical diagram, proposed WMXEC-QDA technique provides betterobject detection accuracy whileincreasing number of sensor nodes as input in network when compared to conventionalMulti-hop decision gathering scheme [1] and P-EETT [2]. This is owing to the application of X-means Ensemble Clustering (XEC) algorithm and Quadratic Discriminant Analysis Based Target Object Detection (QDA-TOD) Algorithmin WMXEC-QDA technique on the contrary to existing works. Hence, the proposedWMXEC-QDA technique enhances the ratio of the number of sensor nodes perfectly give the sensed data regarding the target objects in WSN when compared to state-of-the-art works. Accordingly, theproposedWMXEC-QDA technique increases the object detection accuracy by 10 % and 18 % as compared to traditionalMulti-hop decision gathering scheme [1] and P-EETT [2] respectively.

4.2 Simulation Measure of Object Detection Time

In WMXEC-QDA technique, object detection time 'ODT' measures an amount of time utilized for identifying the target objects in the wireless network. The object detection time is mathematically determined as,

$$ODT = Time_{ED} - Time_{ST} \quad (13)$$

From the above mathematical expression (13), '$Time_{ED}$' and'$Time_{ST}$' indicates an ending time and a starting time of target object detection process. Theobject detection time is determined in terms of milliseconds (ms).

Sample calculation for Object Detection Time:

- ✓ **Proposed WMXEC-QDA technique:** Let us consider the number of sensor nodes is 50. Starting time of object discovery is 0ms and ending time is 8ms. Then the object detection time is estimated as follows,

$$ODT = 8ms - 0ms = 8ms$$

- ✓ **Existing Multi-hop decision gathering scheme:**Starting time of object identification is 0ms and ending time is 15ms. Then the object detection time is computed as follows,

$$ODT = 15ms - 0ms = 15ms$$

- ✓ **Existing P-EETT:** Starting time of object detection is 0ms and ending time is 21ms. Then the object detection time is obtained as follows,

$$ODT = 21ms - 0ms = 21ms$$

The performance result of object detection time with respect to varied number of sensor nodes in the range of 50-500 using three methods namely WMXEC-QDA technique and state-of-the-art Multi-hop decision gathering scheme [1] and P-EETT [2] is depicted in below Table 2. When accomplishing experimental process using 350 sensor nodes, proposed WMXEC-QDA technique takes27 msobject detection timewhereas state-of-the-art Multi-hop decision gathering scheme [1] and P-EETT [2] obtains34 ms and 40 ms respectively. Therefore, it is expressive that the object detection time in WSN using proposed WMXEC-QDA technique is very minimal when compared to other existing works.

Table 3 Tabulation result of Object Detection Time

Number of sensor nodes	Object Detection Time (ms)		
	WMXEC-QDA technique	Multi-hop decision gathering scheme	P-EETT
50	8	15	21
100	11	18	24
150	13	20	25
200	18	26	32
250	20	27	33
300	25	33	38
350	27	34	40

400	30	37	42
450	32	40	46
500	35	42	49

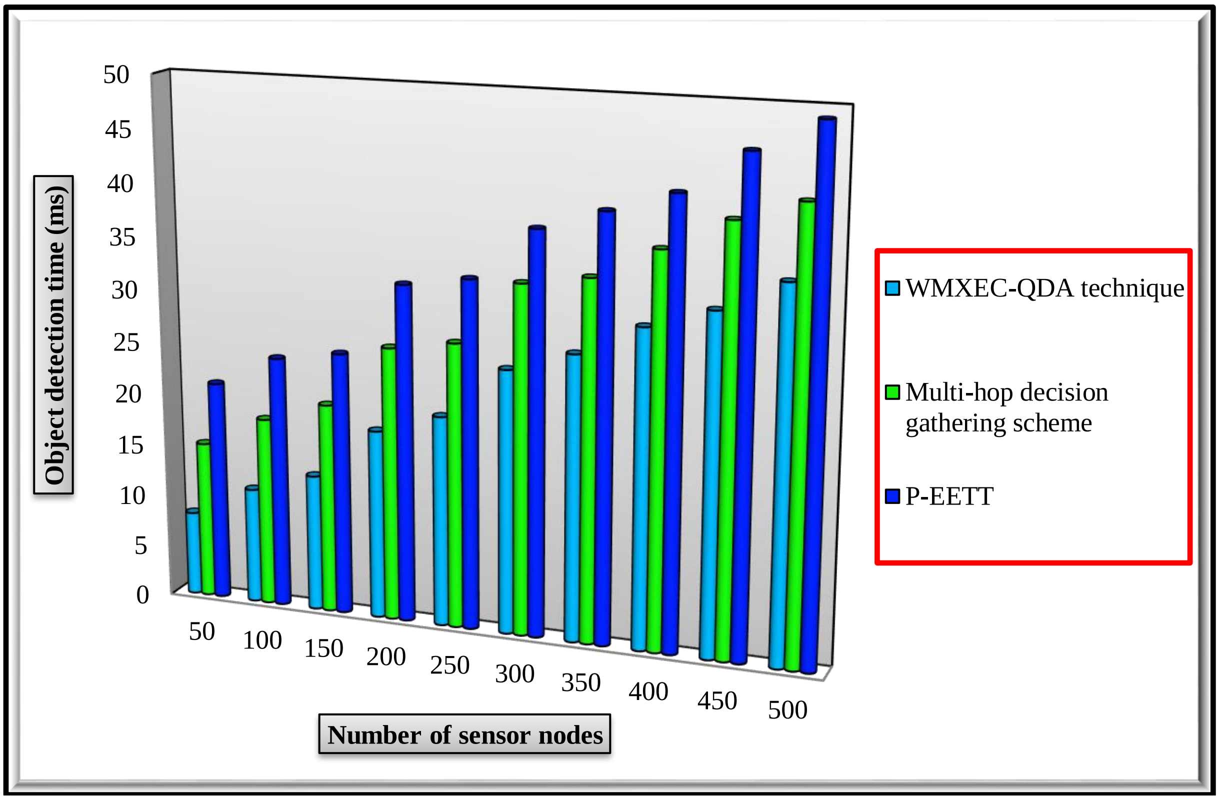

Figure 4 Graphical Result of Object Detection Time versus Number of Sensor Nodes

Figure 4portrays the graphical result of object detection timeaccording to a various number of sensor nodes for three methods namely WMXEC-QDA technique, Multi-hop decision gathering scheme [1] and P-EETT [2]. As shown in the above graphical diagram, proposed WMXEC-QDA technique provides better object detection time while increasing number of sensor nodes as input in network when compared to existing Multi-hop decision gathering scheme [1] and P-EETT [2]. This is because of the application of X-means Ensemble Clustering (XEC) algorithm and Quadratic Discriminant Analysis Based Target Object Detection (QDA-TOD) Algorithm in WMXEC-QDA technique on the contrary to state-of-the-art works. Thus, the proposed WMXEC-QDA technique reduces an amount of time consumed for identifying the target objects in the wireless network when compared to conventional works. For that reason, the proposed WMXEC-QDA technique decreases the object detection time by 28 % and 40 % when compared to traditional Multi-hop decision gathering scheme [1] and P-EETT [2] respectively.

4.3 Simulation Measure of False Positive Rate

In WMXEC-QDA technique, False Positive Rate 'FPR' calculates ratio of a number of sensor nodes incorrectly provides the data regarding target objects in a network to the total number of sensor nodes. The false positive rate is mathematically evaluated as,

$$FPR = \frac{K_{IPD}}{n} * 100 \qquad (14)$$

From the above mathematical formula (14), 'K_{IPD}' indicates to number of sensor nodes inaccurately provides the sensed data about the target objects and 'n' designates a total number of sensor nodes in WSN. The false positive rate is computed in terms of percentage (%).

Sample Calculation for False Positive Rate:

- ✓ **Proposed WMXEC-QDA technique:** Number of sensor nodes is 50 and the number of sensor nodes wrongly provide the sensed data is 2. The false positive rate is measured as follows,

$$FPR = \frac{2}{50} * 100 = 4\%$$

- ✓ **ExistingMulti-hop decision gathering scheme:** Number of sensor nodes is 50 and the number of sensor nodes erroneously give the sensed data is 8. The false positive rate is determined as follows,

$$FPR = \frac{8}{50} * 100 = 16\%$$

- ✓ **Existing P-EETT:** Number of sensor nodes is 50 and the number of sensor nodes mistakenlyprovide the sensed data is 13. The false positive rate is acquired as follows,

$$FPR = \frac{13}{50} * 100 = 26\%$$

The experimental result of false positive rate along with varied number of sensor nodes in the range of 50-500 using three methods namely WMXEC-QDA technique and state-of-the-art Multi-hop decision gathering scheme [1] and P-EETT [2] is depicted in below Table 2. When accomplishing experimental process using 350 sensor nodes, the false positive rate of proposed WMXEC-QDA technique is 9% whereas state-of-the-art Multi-hop decision gathering scheme [1] and P-EETT [2] obtains 15% and 17% respectively. Therefore, it is expressive that the false positive rate in WSN using proposed WMXEC-QDA technique is very minimal when compared to other state-of-the-art works.

Table 4 Tabulation Result of False Positive Rate

Number of sensor nodes	False Positive Rate (%)		
	WMXEC-QDA technique	Multi-hop decision gathering scheme	P-EETT
50	4	16	26
100	3	15	24
150	5	13	21
200	8	16	20
250	9	14	19
300	7	14	20
350	9	15	17
400	8	17	19
450	10	18	21

500	7	18	22

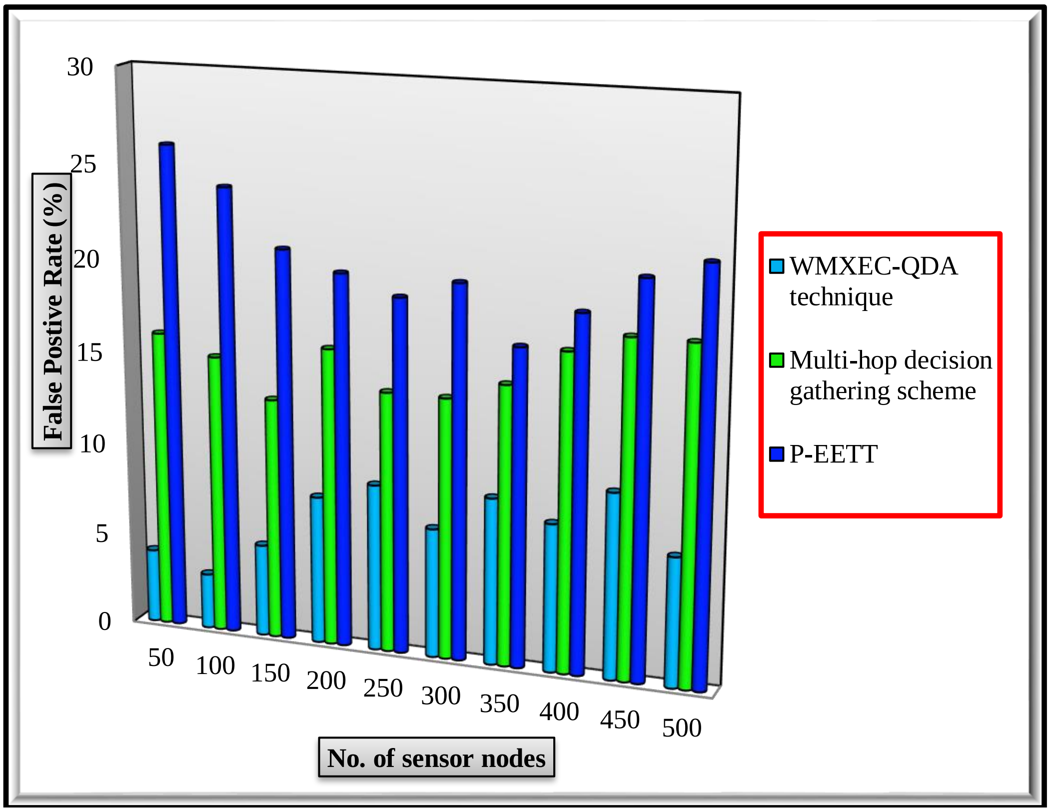

Figure 5 Graphical Result of False Positive Rate versus Number of Sensor Nodes

Figure 5 describes the graphical result of false positive rate of target object detectionalong with a different number of sensor nodes for three methods namely WMXEC-QDA technique, Multi-hop decision gathering scheme [1] and P-EETT [2]. As exposed in the above graphical diagram, proposed WMXEC-QDA technique provides better false positive rate while increasing number of sensor nodes as input in network when compared to traditional Multi-hop decision gathering scheme [1] and P-EETT [2]. This is due to the application of X-means Ensemble Clustering (XEC) algorithm and Quadratic Discriminant Analysis Based Target Object Detection (QDA-TOD) Algorithm in WMXEC-QDA technique on the contrary to conventional works. From that, the proposed WMXEC-QDA technique minimizesratio of a number of sensor nodes incorrectly gives the sensed data about target objects in a network when compared to conventional works. Therefore, the proposed WMXEC-QDA technique diminishes the false positive rate by 55 % and 65 % as compared to conventional Multi-hop decision gathering scheme [1] and P-EETT [2] respectively.

4.4 Simulation Measure of Energy Usage

In WMXEC-QDA technique, energy usage 'EU' measures an amount of energy taken by the sensor nodes to detect the target object in the WSN. The energy usage is mathematically estimated as follows,

$$EU = n * energy\ (SSN) \qquad (15)$$

From the above mathematical formulation (15), '$energy\ (SSN)$'signifies energy used by the single sensor node for identifying the target objects in wireless network whereas 'n'represents a total number of sensor nodes in a network. The energy usage is determined in terms of a joule (J).

Sample calculation for Energy Usage

- ✓ **Proposed WMXEC-QDA technique:**number of sensor nodes is 50 and the energyemployed by one sensor nodes is 0.3Joule. The energy usage is calculated as follows,

$$EU = 50 * 0.3 = 15\,J$$

- ✓ **Existing Multi-hop decision gathering scheme:**number of sensor nodes is 50 and the energyutilized by one sensor nodes is 0.4Joule. The energy usage is computed as follows,

$$EU = 50 * 0.4 = 20\,J$$

- ✓ **Existing P-EETT:**number of sensor nodes is 50 and the energyconsumed by one sensor nodes is 0.5Joule. The energy usage is measured as follows,

$$EU = 50 * 0.5 = 25\,J$$

The tabulation result of energy consumptionduring the processes of target object detection in WSN based on different number of sensor nodes in the range of 50-500 using three methods namely WMXEC-QDA technique and traditional Multi-hop decision gathering scheme [1] and P-EETT [2] is shown in below Table 3. When performing experimental evaluation using 400 sensor nodes, proposed WMXEC-QDA technique obtains 36Jenergy whereas conventional Multi-hop decision gathering scheme [1] and P-EETT [2] gains 46J and 50J respectively. As a result, it is clear that the energy usage in WSN using proposed WMXEC-QDA technique is very minimal when compared to other conventional works.

Table 5 Tabulation Result of Energy Usage

Number of sensor nodes	Energy Usage (J)		
	WMXEC-QDA technique	Multi-hop decision gathering scheme	P-EETT
50	15	20	25
100	19	22	28
150	23	27	32
200	24	30	36
250	28	33	39
300	30	36	42
350	34	45	46
400	36	46	50
450	42	49	54
500	44	51	56

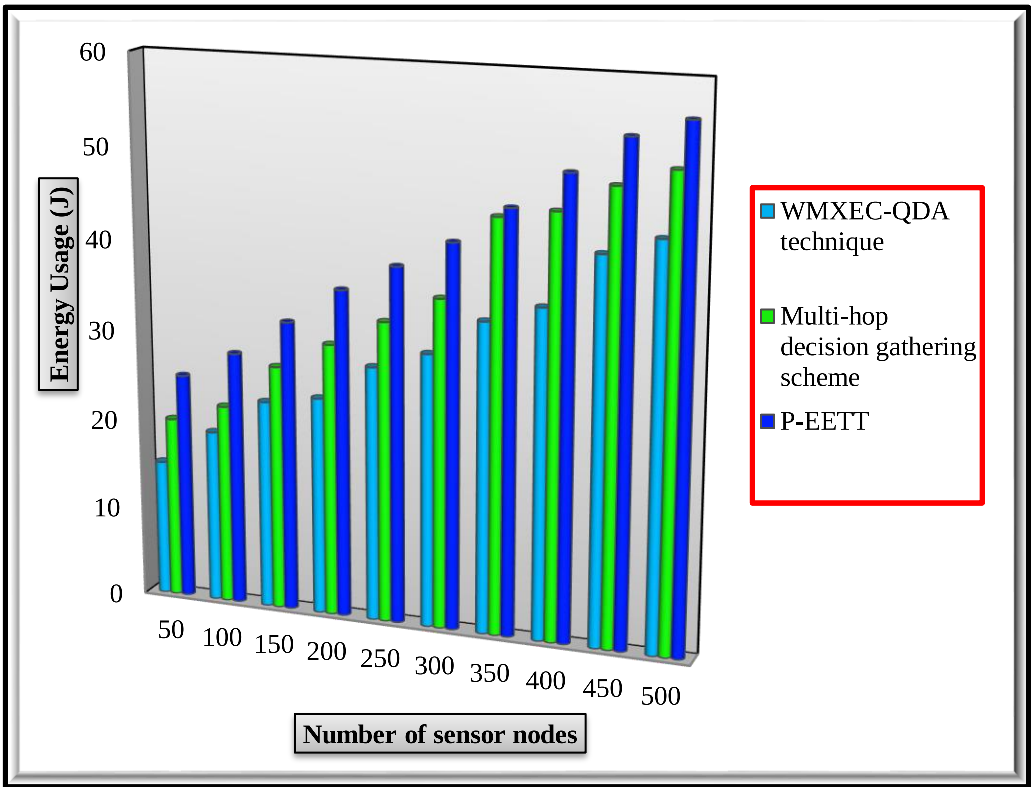

Figure 6 Graphical Result of Energy Usage versus Number of Sensor Nodes

Figure 6 illustrates the graphical result of energy utilization of target object discovery with respect to a dissimilar number of sensor nodes for three methods namely WMXEC-QDA technique, Multi-hop decision gathering scheme [1] and P-EETT [2]. As presented in the above graphical illustration, proposed WMXEC-QDA technique provides better energy consumption to accurately find the target objects while increasing number of sensor nodes as input in network when compared to traditional Multi-hop decision gathering scheme [1] and P-EETT [2]. This is because of the application of X-means Ensemble Clustering (XEC) algorithm and Quadratic Discriminant Analysis Based Target Object Detection (QDA-TOD) Algorithm in WMXEC-QDA technique on the contrary to existing works. Accordingly, the proposed WMXEC-QDA technique decreases an amount of energy required by the sensor nodes to identify the target object in the WSN when compared to conventional works. As a result, the proposed WMXEC-QDA technique reduces the energy usage by 18 % and 29 % as compared to conventional Multi-hop decision gathering scheme [1] and P-EETT [2] respectively.

5. LITERATURE SURVEY

Probability-Based Prediction and Sleep Scheduling was performed in [11] for accomplishing energy-efficient target tracking in sensor networks. However, computational time taken for target object detection was more. An energy-efficient incremental clustering algorithm was designed in [12] for accurate localization of dynamic objects in the sensor network. But, energy usage using this algorithm was higher.

Data fusion was employed in [13] for accurate target discovery in maritime search and rescue WSN.However, false positive rate using this algorithm was higher. An Integer Linear Programming model was introduced in [14] for performing multi-target tracking in heterogeneous WSNs. But, object detection time using this model was not minimized.

A survey of different techniques designed for accomplishing target tracking process in WSN was presented in [15]. A hybrid density and distance based clustering method was presented in [16] for minimizing the misdetection in multi-target problem. However, accuracy using this model was not higher.

An enhanced Object Localization was employed in [17] with help of accurate distance estimation in wireless multimedia sensor networks. But, resource efficient target object detection was not attained. Convolution neural network (CNN)-based method was presented in [18]for efficient tracking of multi-target objects with higher accuracy. However, time complexity using CNN was more.

A fuzzy c-means clustering approach was introduced in [19] for reducing the false positive rate of the target detection. But, the target detection time was not reduced. Collaborative fusion was employed in [20] to reduce the latency of target detection. However, energy consumed for detection process was higher.

6. CONCLUSION

The WMXEC-QDA technique is intended with the objective of improving the performance of target objects detection in WSN with minimal amount of energy. The objective of WMXEC-QDA technique is attained by using the X-means Ensemble Clustering (XEC) and Quadratic Discriminant Analysis Based Target Object Detection (QDA-TOD) Algorithms on the contrary to conventional works. The proposed WMXEC-QDA technique enhances the ratio of the number of sensor nodes accurately give the sensed data about the target objects in WSN when compared to traditional algorithms. As well, the proposed WMXEC-QDA technique minimizes an amount of time utilized for identifying the target objects in the wireless network when compared to state-of-the-art works. Also, proposed WMXEC-QDA technique decreases ratio of a number of sensor nodes incorrectly gives the sensed data about target objects in a network when compared to conventional works. Further, proposed WMXEC-QDA technique reduces an amount of energy required by the sensor nodes to discover the target object in the WSN when compared to traditional works. The performance of WMXEC-QDA technique is calculated in terms of object detection accuracy, object detection time, and energy usage, false positive rate and compared with two conventional works.The simulation result illustrates that WMXEC-QDA technique provides better target objects detection performance with an improvement of accuracy and minimization of energy consumption when compared to state-of-the-art works.

References

[1] Saud Althunibat, Ziyad Al Tarawneh, “Multi-hop decision gathering scheme for target-detection wireless sensor networks”, IET Communications, Volume 13, Issue 19, Pages 3278-3284, 2019

[2] J. RejinaParvin, C.Vasanthanayaki, “Particle swarm optimization-based energy efficient target tracking in wireless sensor network”, Measurement, Elsevier, Volume 147, Pages 1-8, December 2019

[3] AsmaEnayet, Md. AbdurRazzaque,MohammadMehediHassan,AhmadAlmogren, and AtifAlamri, “Moving Target Tracking through Distributed Clustering in Directional Sensor Networks”, Volume 14, Issue 12, Pages 24381–24407, 2014

[4] S.M. Hosseini, M.H. Kahaei, “Target detection in cluster based WSN with massive MIMO systems”, Electronics Letters, Volume 53, Issue 1, Pages 50-52, 2017

[5] Zhiyong Wei, Fengling Wang, “Adaptive cascade single-shot detector on wireless sensor networks”, EURASIP Journal on Wireless Communications and Networking, Springer, Volume 150, Pages 1-13, December 2019

[6] ZhiboWang, Wei Lou, ZhiWang, JunchaoMa, and Honglong Chen, “A Hybrid Cluster-Based Target Tracking Protocol for Wireless Sensor Networks”, Hindawi Publishing Corporation, International Journal of Distributed Sensor Networks, Volume 2013, Article ID 494863, Pages 1-16, 2013

[7] Efren L. Souza, Richard W. Pazzi, Eduardo F. Nakamura, “A prediction-based clustering algorithm for tracking targets in quantized areas for wireless sensor networks”, Wireless Networks, Springer, Volume 21, Issue 7, Pages 2263–2278, October 2015

[8] Mohamed Toumi, AbderrahimMaizate, Mohammed Ouzzif, andMed Said Salah, “Dynamic Clustering Algorithm for Tracking Targets with High and Variable Celerity (ATHVC)”, Journal of Computer Networks and Communications, Hindawi Publishing Corporation, Volume 2016, Pages 1-10, October 2016

[9] Chunming Wu, Chen Zhao &Haoquan Gong, “Energy-Efficient Target Tracking Algorithm for WSNs”, 3D Research, Springer, Volume 10, Issue 1, 2018

[10] Gu D, “A game theory approach to target tracking in sensor networks”, IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), Volume 41, Issue 1, Pages 2-13, 2011

[11] Bo Jiang, BinoyRavindran, Hyeonjoong Cho, “Probability-Based Prediction and Sleep Scheduling for Energy-Efficient Target Tracking in Sensor Networks”, IEEE Transactions on Mobile Computing, Volume 12, Issue 4, Pages 735 – 747, April 2013

[12] MahmudaAkter, Md. Obaidur Rahman, Md. Nazrul Islam, Mohammad Mehedi Hassan, Ahmed Alsanad And Arun Kumar Sangaiah, “Energy-Efficient Tracking and Localization of Objects in Wireless Sensor Networks”, IEEE Access, Volume 6, Pages 17165-17177, 2018

[13] Huafeng Wu, Jiangfeng Xian, Xiaojun Mei, Yuanyuan Zhang, Jun Wang, Junkuo Cao, PrasantMohapatra, “Efficient target detection in maritime search and rescue wireless sensor network using data fusion”, Computer Communications, Elsevier, Volume 136, Pages 53-62, February 2019

[14] MarjanNaderan, Mehdi Dehghan, Hossein Pedram, “Upper and lower bounds for dynamic cluster assignment for multi-target tracking in heterogeneous WSNs”, Journal of Parallel and Distributed Computing, Elsevier, Volume 73, Issue 10, Pages 1389-13, October 2013

[15] AsmaaEz-Zaidi and Said Rakrak, “A Comparative Study of Target Tracking Approaches in Wireless Sensor Networks”, Journal of Sensors, Volume 2016, Pages 1-11, 2016

[16] Tiancheng Li, FernandoDe la PrietaPintado, Juan M.Corchadoa Javier Bajo, “Multi-source homogeneous data clustering for multi-target detection from cluttered background with misdetection”, Applied Soft Computing, Elsevier, Volume 60, Pages 436-446, November 2017

[17] Yasar Abbas Ur Rehman,Muhammad Tariq ,Omar Usman Khan, “Improved Object Localization Using Accurate Distance Estimation in Wireless Multimedia Sensor Networks”, PLoS ONE, Volume 10, Issue 11, 2015

[18] Sang-Hyeon Kim, Han-Lim Choi, “Convolutional Neural Network for Monocular Vision-based Multi-target Tracking”, International Journal of Control, Automation and Systems, Springer, Volume 17, Issue 9, Pages 2284–2296, September 2019

[19] Jing Liang, Yaoyue Hu, Huaiyuan Liu, Chengchen Mao, “Fuzzy clustering in radar sensor networks for target detection”, Ad Hoc Networks, Elsevier, Volume 58, Pages 150-159, 2017

[20] Tai-Lin Chin and Wan-Chen Chuang, “Latency of Collaborative Target Detection for Surveillance Sensor Networks”, IEEE Transactions on Parallel and Distributed Systems, Volume 26, Issue 2, Pages 467 – 477, 2015