Resource Aware Bagging Cluster Based Robust Linear Regression Analysis for Sensed Target Object Detection in Wsn

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ABSTRACT:

Target object detection is one of key problem to be resolved in wireless sensor networks (WSN) as it attains great attention. Target detection in WSN is a difficult process. Because sensor nodes contain limited battery power, high mobility of nodes and unpredictable environments, etc. For target object detection, few research works have been introduced in WSN. However, the target detection accuracy was not enough. To overcome such existing issues, Bagging Mean-shift Cluster-Based Robust Linear Regression (BMC-RLR) technique is proposed. Initially, numbers of sensor nodes are arbitrarily deployed in WSN.Next, BMC-RLR technique employs bagging clustering technique i.e. Resource Aware Mean-shift Bagging Cluster (RAMBC) that builds 'n' number of weak mean shift clusters for each input numbers of sensor nodes. Then, RAMBC in BMC-RLR technique combines all mean shift clusters by applying a voting scheme and thereby designs a strong cluster with minimal error.. By using a strong cluster, the sensor nodes are grouped into various clusters with higher accuracy. In BMC-RLR Technique, the sensor node with higher residual energy is selected as cluster head (CH) to carry out resource aware data aggregation and target object discovery. CH collects data of target objects and broadcast to sink node. Sink node forwards sensed data to the base station where it employs Robust Linear Regression Analysis (RLRA) in order to accurately discover the target objects within the network. This helps for BMC-RLR technique to increases the TDA in WSN. Simulation of BMC-RLR technique is conducted with metrics namely TDA, target detection time (TDT), error rate (ER) and energy consumption (EC) with number of sensor nodes.

Keywords: Base station, cluster head, means shift cluster, residual energy, Robust Linear Regression Analysis, strong cluster, target object

1. INTRODUCTION

Target object detection is one of the most significant topics in WSN. Minimizing energy utilization in target object detection is a difficult problem as sensor nodes are constrained in terms of energy. In existing works, many research works have been designed to find the target objects in WSN using different techniques. But, the TDA was not sufficient. Besides, time taken for target object discovery is also higher. Therefore, a novel BMC-RLR technique is introduced in this research work. An Incremental Clustering-Based Tracking was designed in [1] with the help of Gaussian adaptive resonance theory for performing energy efficient target-discovery in WSN. However, clustering performance was not sufficient to achieve higher target object detection performance. An Index Modulation for Cluster-Based

Wireless Sensor Networks called (IM-WSN) was developed in [2] for target-detection. But, the amount of time required for identifying the target object was higher.

Hierarchical prediction strategy (HPS) was introduced in [3] to accomplish energy-efficient target tracking in WSNs. But, EC was more. An innovative target tracking algorithm was designed in [4] with the application of learning regression tree approach. However, TDA was not at the required level. In [5], An Energy-Efficient Constant Gain Kalman Filter-based Tracking (EECGKFT) algorithm was presented to lessen the time complexity in the target detection process. But, the ER was more. For energy-efficient target discovery, a Laceration-localizing Algorithm was designed in [6]. The TDA was poor. A global profile-based algorithm was applied in [7] for object detection in WSN. But accuracy was not improved. The fuzzy model and Generalized Kalman Filter were employed in [8] with the aim of carried outing energy efficient target tracking. However the number of target objects incorrectly detected was higher. In [9], Coordinated and adaptive information collecting strategy (CAICS) was presented for target tracking and data collection. However, energy efficient target detection was not obtained. An adaptive-head clustering algorithm was presented in [10] to attain impressive tracking quality and energy efficiency in WSN. But, this algorithm takes more time for target detection.
BMC-RLR technique is proposed to overcome the aforesaid existing issues. Contributions of BMC-RLR technique are explained below,

- To obtain higher clustering accuracy for efficient target object detection in WSN as compared to conventional works, RAMBC is designed in BMC-RLR technique. The RAMBC is a machine learning technique where multiple cluster results are combined to generate strong clustering result. In RAMBC, input sensor nodes are clustered based on the majority vote predicted by the ensemble. Thus, RAMBC accomplishes efficient clustering process in WSN with minimal time.

- To achieve higher TDA as compared to conventional works, RLRA is utilized in BMC-RLR technique. RLRA is a Powerful statistical method that examines the relationship between sensed data to correctly find target objects in the network.

The rest of article is ordered as follows: BMC-RLR technique is described in Section 2 with assist of architecture diagram. Simulation settings and result discussion are described in Section 3 and Section 4 respectively. Related works are explained in Section 5. Conclusion of article is depicted in Section 6.

2. PROPOSED METHODOLOGY

Let us consider WSN with squared sensing area represented as '$K \times K$' where the sensor nodes are randomly organized. Besides, WSN denoted as a graph structure '$G = (A, B)$' in which 'A' refers a sensor nodes '$S_1, S_2, S_3, .., S_n$' and 'B' indicates a set of links between the sensor nodes. Here, sensor nodes are grouped into diverse clusters for efficient target object discovery in WSN. In order to increases the target object identification performance with a lower time complexity, BMC-RLR technique is introduced in this research work. BMC-RLR technique is designed by combining the RAMBC and RLRA algorithms.

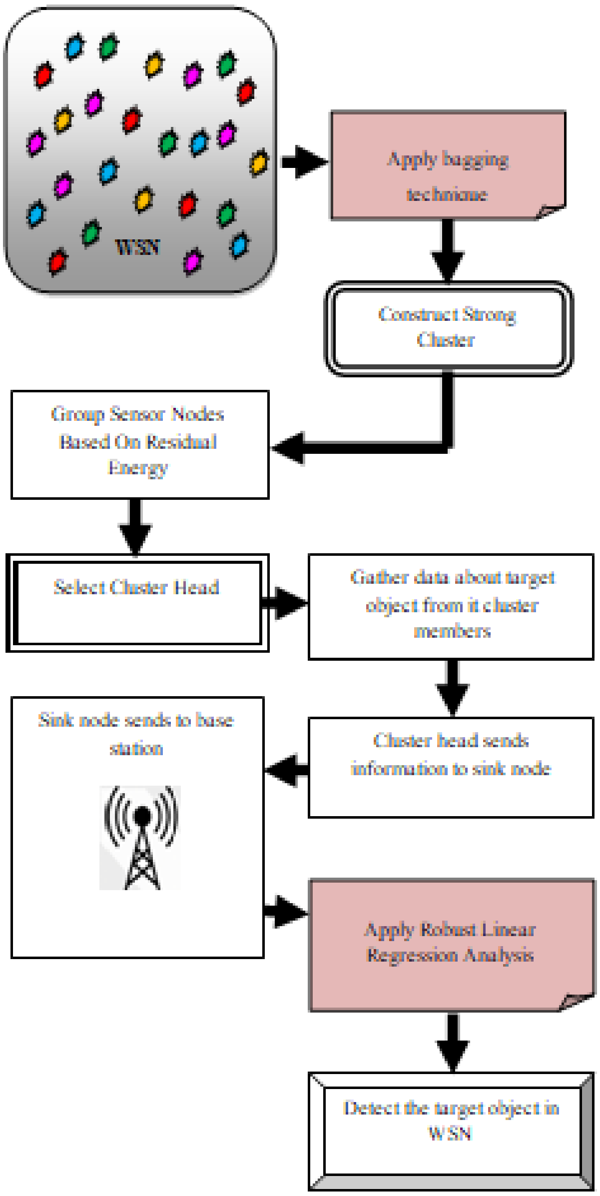

Figure 1 BMC-RLR Technique for Target Object Detection in WSN

Figure 1 shows the overall processes of the BMC-RLR Technique to find out the target object. Sensor nodes are located in the sensing area. Next, the bagging technique is employed in BMC-RLR Technique to construct strong cluster with aiming at grouping sensor nodes depends on their energy level. CH is chosen to collects the data of target objects and send these data to base station for detecting target objects in WSN. At the base station, BMC-RLR Technique carried out RLRA with collected data and thereby exactly finds the target objects in WSN.

2.1 Resource Aware Mean-shift Bagging Cluster For Data Aggregation

In BMC-RLR technique, RAMBC is proposed with the objective of increasing accuracy of node clustering for efficient data aggregation during target object detection process. The RAMBC is a machine learning ensemble algorithm. The RAMBC is designed by combining the mean-shift clustering and bootstrap aggregation (i.e. bagging method) on the contrary to conventional works to get better data aggregation performance in WSN. In RAMBC, mean shift clustering is considered as weak cluster. The conventional mean shift clustering group the sensor nodes into a different cluster. But, clustering accuracy was not adequate to efficiently carried out the data aggregation process. In order to solve this drawback, RAMBC is proposed in BMC-RLR technique via integrating the number of weak Mean Shift clustering results into a strong cluster. In RAMBC, strong cluster is designed to cluster the sensor nodes depends on their residual energy into diverse clusters with minimal time.

Consider a number of sensor nodes is denoted as '$S_1, S_2, S_3, .., S_n$' where 'n' indicates a total number of sensor nodes considered to perform data aggregation. RAMBC designs a number of weak mean shift clusters to group the sensor according to their residual energy. The weak mean shift cluster is employed in RAMBC is a centroid-based algorithm. Based on number of sensor nodes, the number of clusters is determined. The weak mean shift cluster groups the each sensor nodes to the mean (i.e. centroids) of the cluster. From that, the mean 'τ' is determined for all cluster with help of below mathematical formula,

$$\tau = \frac{1}{n} \sum_{i=1}^{n} S_i \qquad (1)$$

From equations (1), 'τ' denotes a mean of the cluster and 'S_i' indicates the sensor node. In the weak mean shift cluster, the mean is measured as weighted average of the residual energy of sensor nodes within a cluster. In WSN, energy level of the sensor nodes are gets reduced according to their capability of environmental sensing because sensor nodes are battery powered. Therefore, the sensor node residual energy is significant for resource aware target object detection with higher energy efficiency. On the contrary to conventional works, the resource factor i.e. residual energy of sensor node is taken to increase the network lifetime. Thus, residual energy is mathematically measured using below expression,

$$\alpha_{\varepsilon\,(S)} = \varepsilon_{total} - \varepsilon_{consumed} \qquad (2)$$

From (2), '$\alpha_{\varepsilon\,(S)}$' denotes the residual energy of sensor node. Here, 'ε_{total}' denotes the total energy (i.e. initial energy) of sensor nodes in WSN and '$\varepsilon_{consumed}$' represents the amount of energy consumed for sensing data in a network. From (2), RAMBC calculates residual energy of each sensor nodes. After that, the nearby senor nodes are grouped using below equation,

$$GKF\,(S, \tau_i) = \exp\left(-\frac{\|\tau_i - S\|^2}{2\,a^2}\right) \qquad (3)$$

From the above mathematical formulations (3), 'GKF' point outs a Gaussian kernel function. '$\|\rho_i - S\|^2$' denotes the squared distance between sensor node and cluster mean and 'a' specifies a deviation from its mean. During the each iteration, each sensor node in a WSN is grouped into a nearest cluster mean. The process of weak mean shift cluster is recurrent until all the sensor nodes are grouped into the clusters. The node clustering accuracy of weak mean shift cluster is not enough to achieve better target objection detection performance. Therefore, the bagging method is applied in RAMBC in order to further enhance the clustering performance of weak mean shift cluster.

With the help of a bagging method (i.e. bootstrap aggregation), RAMBC generates a number of bootstrap samples initially using sensor nodes in WSN. A bootstrap sample is a tiny sample which is generated by considering a larger number of sensor nodes in WSN. Followed by, RAMBC build 'n' number of weak mean shift cluster results for each sensor node in bootstrap samples. Next, RAMBC ensembles all weak mean shift cluster results using below mathematical equation,

$$W(S_i) = W_1(S_i) + W(S_i) + \cdots + W_n(S_i) \qquad (4)$$

Consequently, RAMBC apply vote 'v_i' for each weak mean shift cluster results '$W(S_i)$' with help of mathematical expression,

$$v_i \rightarrow \sum_{i=1}^{n} W(S_i) \qquad (5)$$

Thus, majority vote of each weak mean shift cluster results are combined to create strong cluster which grouping the sensor nodes depends on their residual energy. From that, strong clustering output is mathematically obtained using below,

$$Z\,(S_i) = arg \max_{n} v(W(S_i)) \qquad (6)$$

From equation (6), '$Z\,(S_i)$' denotes the final strong clustering result to group the sensor nodes depends on residual energy. Here, '$arg \max_{n} v$' refers majority votes of weak mean shift cluster output. With assist of strong cluster, RAMBC group sensor nodes depend on their residual energy. After the clustering process, RAMBC discovers CH for each cluster in network. In RAMBC, each cluster contains one CH and many member nodes where CH gathering data about target node from the cluster members and sent aggregated data to the base station for carried outing target detection. Therefore, RAMBC chooses sensor node with greater residual energy within the cluster as a CH for data aggregation in WSN.

The algorithmic process of RAMBC is described for effective data aggregation in WSN during target objects detection.

//Resource Aware Mean-shift Bagging Clustering Algorithm
Input: Number Of Sensor Nodes '$S_1, S_2, S_3, \ldots S_n$'
Output: groups the vehicle nodes into a different cluster
Step 1: Begin
Step 2: For each number of input sensor nodes 'S_n'
Step 3: Generate bootstrap samples with sensor nodes
Step 4: For each sensor node 'S_i'
Step 5: Determine the residual energy level using (2)
Step 6: Create 'n' number of weak mean shift cluster results
Step 7: Unites all the weak mean shift cluster results using (4)
Step 8: Apply a voting scheme using (5)
Step 9: Get strong clustering output using majority votes using (6)
Step 10: Strong cluster correctly groups sensor nodes into a diverse cluster
Step 11: End For
Step 12: End For
Step 13: For each cluster
Step 14: Discover a sensor node with higher residual energy as a cluster head
Step 15: End For
Step 16: Cluster head collects data about target objects from its members
Step 17: Cluster head forwards gathered data to sink node
Step 18: Sink node get gathered data and transmit it to the base station
Step 19:End

Algorithm 1 Resource Aware Mean-shift Bagging Clustering

As demonstrated in the above algorithmic steps, RAMBC at first takes a number of sensor nodes as input and subsequently, RAMBC creates a number of bootstrap samples. For each sensor node in bootstrap samples, after that RAMBC produces 'n' number of weak mean shift cluster results. Followed by, RAMBC ensembles the result of all weak mean shift cluster results. Subsequently, RAMBC applies the voting scheme. Afterward, RAMBC develops strong cluster by using majority votes of weak mean shift cluster results. The created strong cluster groups the sensor nodes into dissimilar clusters based on measured residual energy. For each cluster, the RAMBC identifies higher residual energy node as a CH where it aggregates data regarding target object which entered into a network from its cluster member. Then, CH transmits collected data to base station though a sink node for detecting the target objects in WSN.

2.2 Robust Linear Regression Analysis for Target Object Detection

After getting the collected data regarding target objects, the base station performs RLRA in order to increase the accuracy of target object discovery in WSN with minimal time. On the contrary to existing works, RLRA is a significant tool for modeling and analyzing data. This helps for BMC-RLR technique for efficient target object identification in a wireless network. RLRA is a machine learning algorithm depends on supervised learning. In BMC-RLR technique, RLRA carried outs a regression task. RLRA finds a target objects in WSN based on gathered information at the base station through identifying the relationship between input data.

In machine learning algorithms, the RLRA discovers the relations among dependent and one or more independent variables. Here, the independent variables are collected information's by sensor nodes about the target node and the dependent variable is the output (i.e. target node or not). The process involved in RLRA is shown in below Figure 2.

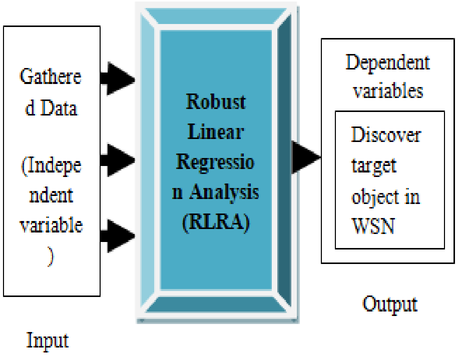

Figure 2 Processes of Robust Linear Regression Analysis

From figure 2, RLRA carry outs regression task to predict dependent variable value 'y' (i.e. target object) based on independent variable 'x' (i.e. collected data at base station). From that, RLRA is mathematically carried out using below expression,

$$y = \omega_1 + \omega_2 . x \qquad (7)$$

From the above mathematical formulation (7), 'y' signifies a labels to data (i.e. target object or not) and 'x' represents input training data (i.e. collected data about target objects at sink node). When training the model, RLRA fits the best line to determine the value of 'y' for a given value of 'x'. The RLRA gets the best regression fit line through finding the best 'ω_1' and 'ω_2' values. Here, 'ω_1' represent intercept whereas 'ω_2' denotes coefficient of 'x'. After discovering the best 'ω_1' and 'ω_2' values, RLRA get the best fit line. From that, RLRA find the value of 'y' for the input value of 'x'. Based on this value, the base station makes a decision regarding the target node in WSN. By this way, base station significantly finds the target object in a network using RLRA.

By achieving the best-fit regression line, the RLRA aims to discover 'y' value such that the error distinction between predicted output and true output is minimum. Therefore it is very important to update the 'ω_1' and 'ω_2' values to attain the best value that reduce the error between detected output and true output using below mathematical formula,

$$\varepsilon = \frac{1}{n}\sum_{i=1}^{n}(P_O - T_O) \qquad (8)$$

From (8), error function 'ε' of RLRA is the Root Mean Squared Error (RMSE) between predicted output 'P_O' and true output 'T_O'. RLRA updates 'ω_1' and 'ω_2' values to decrease error function and thereby achieving the best fit line with application of Gradient Descent using below,

$$y = \arg\min \frac{1}{n} \sum_{i=1}^{n} (P_O - T_O) \qquad (9)$$

By using the above equation (9), RLRA accurately detects target objects in WSN with a minimal error function. The target object identification process in WSN using RLRA is presented in below Figure 3.

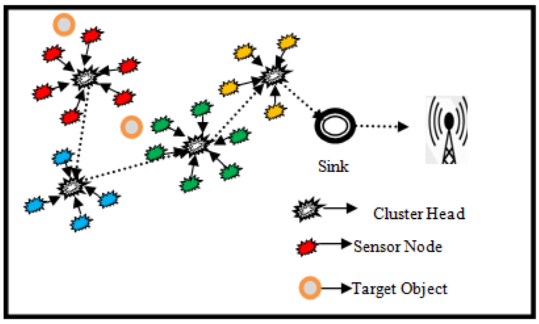

Figure 3 Target Object Detection in WSN using RLRA

Figure 3 depicts the RLRA process for efficiently discovering target object in WSN with a lower amount of time consumption. The algorithmic processes of RLRA is explained in below,

// **Robust Linear Regression Analysis Algorithm**
Input: Collected Data about Target Object '$\mu_1, \mu_2, \mu_3, \ldots, \mu_n$'
Output: Achieve higher target detection accuracy
Step 1: Begin
Step 2: **For** gathered data regarding target object 'μ_i'
Step 3: Perform robust linear regression analysis using (7)
Step 4: Detect target object in WSN
Step 5: Measure error function 'ε' using (8)
Step 6: Minimize error function using (9)
Step 7: **If** '($y == 1$)', **then**
Step 8: Target object in the network is correctly detected
Step 9: **Else**
Step 10: Target object is not detected
Step 11: **End If**

Algorithm 2 Robust Linear Regression Analysis

Algorithm 2 describes the process of RLRA for target object discovery in WSN. By using the above algorithmic process, RLRA precisely discovers the target objects in WSN with minimal time. From that, BMC-RLR technique offers higher TDA as compared to conventional methods.

3. SIMULATION SETTINGS

The performance of BMC-RLR technique is evaluated in NS2.34 Simulator with 500 senor nodes in the sensing network area of 1200 m * 1200 m. Table 1 presents the metrics for simulation evaluation.

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

BMC-RLR technique is evaluated in terms of TDA, TDT and ER and EC with numbers of sensor nodes. Simulation performance of BMC-RLR technique is compared against conventional Incremental Clustering-Based Tracking [1] and IM-WSN [2].

4. RESULTS

The result of BMC-RLR technique is described in this section. Proposed BMC-RLR technique is compared with existing [1] and [2] with the assist of tables and graphs.

4.1 Target Detection Accuracy

In BMC-RLR technique, 'TDA' measures how the base station accurately discovers the target objects in WSN by using sensed data. TDA computed as the ratio of number of sensor nodes correctly send data about target objects to total number of sensor nodes. TDA is determined as follows,

$$TDA = \frac{N_{ASD}}{m} * 100 \qquad (10)$$

From (10), 'N_{ASD}' indicates a number of sensor nodes accurately send collected data of target objects whereas 'm' indicates a total number of sensor nodes. TDA is calculated in percentage (%).

Table 2 Tabulation Result of Target Detection Accuracy

Number of sensor nodes	Target Object Detection Accuracy (%)		
	BMC-RLR	Incremental Clustering-Based Tracking	IM-WSN
50	94	80	70
100	96	83	74
150	93	84	77
200	92	84	79
250	90	83	80
300	89	82	79
350	88	82	80
400	87	81	79
450	85	80	78
500	85	78	76

Table 2 demonstrates the result of TDA.

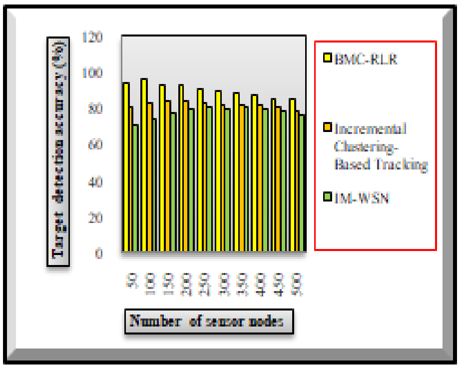

Figure 4 Comparative Result Analysis of Target Detection Accuracy versus Number Of Sensor Nodes

The simulation result of TDA is depicted in figure 4 for three methods. From figure 4, BMC-RLR technique obtains higher TDA as compared to existing [1] and [2]. This is because of the application of RAMBC and RLRA algorithms in BMC-RLR technique. With the concepts of RAMBC and RLRA algorithms, BMC-RLR technique precisely finds target objects in network using collected data through regression. From that, the BMC-RLR technique enhances the ratio of number of target object detected in WSN as compared to conventional works. Thus, BMC-RLR technique improves the TDA by 10 % and 17 % as compared to existing [1] and [2].

4.2 Target Detection Time

In BMC-RLR technique, ‘*TDT*’ calculates an amount of time taken for detecting the target object in the WSN. The TDT is measured as,

$$TDT = t_{ED} - t_{ST} \quad (11)$$

From the above equation (11), 't_{ED}' and't_{ST}' symbolizes an ending time and a starting time of target object identification process and it measured in terms of milliseconds (ms).

Table 3 depicts the result of TDT.

Table 3 Tabulation result of Target Detection Time

Number of sensor nodes	Target Detection Time (ms)		
	BMC-RLR	Incremental Clustering-Based Tracking	IM-WSN
50	10	19	24
100	13	21	26
150	15	24	28
200	20	29	34
250	22	31	35
300	27	36	40
350	29	38	42
400	32	40	45
450	34	44	49
500	37	45	51

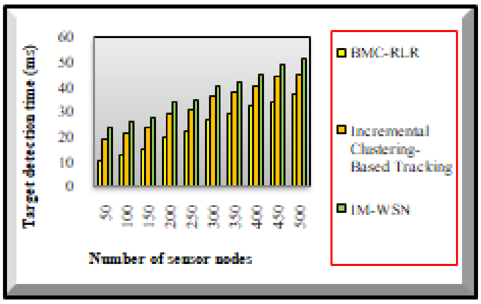

Figure 5 Comparative Result Analysis of Target detection time versus number of sensor nodes

Figure 5 portrays simulation result of TDT based on a different number of sensor nodes using BMC-RLR technique, Incremental Clustering-Based Tracking [1] and IM-WSN [2]. From figure 5, BMC-RLR technique provides lesser TDT as compared to existing [1] and [2]. This is owing to the application of RAMBC and RLRA algorithms in BMC-RLR technique. By applying the RAMBC and RLRA algorithms, proposed BMC-RLR technique identifies target objects in network with minimal time according to sensed data. Therefore, the BMC-RLR technique lessens the TDT by 29 % and 38 % as compared to existing [1] and [2].

4.3 Error Rate

'ER' defined as ratio of a number of sensor nodes incorrectly provides data about target objects to total number of sensor nodes. ER is formalized as,

$$ER = \frac{N_{ISD}}{m} * 100 \qquad (12)$$

From (12), 'N_{ISD}' point outs to number of sensor nodes inaccurately send sensed data about target objects and 'm' specifies a total number of sensor nodes. ER is evaluated in percentage (%).

Table 4 Tabulation result of Error Rate

Number of sensor nodes	Error Rate (%)		
	BMC-RLR	Incremental Clustering-Based Tracking	IM-WSN
50	6	20	30
100	4	17	26
150	7	16	23
200	9	17	21
250	10	17	20
300	11	18	21
350	12	18	20
400	14	19	22
450	15	20	22
500	15	22	24

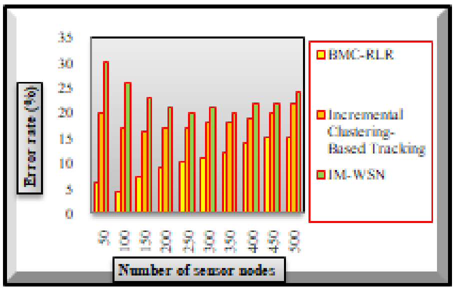

Figure 6 Comparative Result Analysis of Error Rate versus Number of Sensor Nodes

Figure 6 reveals the simulation result of ER along with a varied number of sensor nodes using BMC-RLR technique, Incremental Clustering-Based Tracking [1] and IM-WSN [2]. From figure 6, BMC-RLR technique attains minimal ER as compared to existing [1] and [2]. This is due to the application of RLRA in BMC-RLR technique. With assist of RLRA, the BMC-RLR technique exactly discovers target objects in a network with the help of sensed data. This helps for BMC-RLR technique to lessen the wrong detection of target objects. Therefore, the proposed BMC-RLR technique decreases the ER of target detection by 45 % and 53 % when compared to Incremental Clustering-Based Tracking [1] and IM-WSN [2] respectively.

4.4 Energy Consumption

In BMC-RLR technique, 'EC' calculates as an amount of energy utilized by the sensor nodes to find the target object in the WSN. EC is mathematically evaluated as,

$$EC = m * E\ (SS) \qquad (13)$$

From (13), $E(SS)$ specifies energy taken by single sensor node during target detection process and 'm' denotes a total number of sensor nodes. EC is calculated in joule (J).

Table 5 Tabulation result of Energy Consumption

Number of sensor nodes	Energy Consumption (J)		
	BMC-RLR	Incremental Clustering-Based Tracking	IM-WSN
50	20	23	28
100	21	25	30
150	26	30	35
200	26	34	40
250	30	38	44
300	33	42	48
350	37	48	50
400	40	50	55
450	46	54	59
500	49	56	61

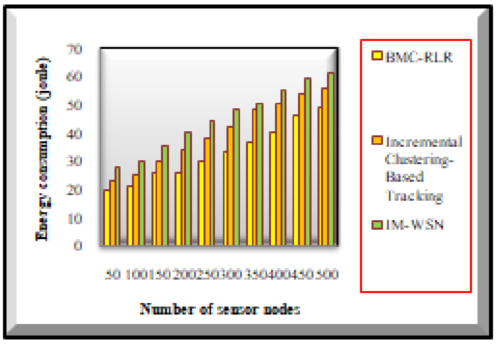

Figure 7 Comparative Result Analysis of Energy Consumption versus number of sensor nodes

Simulation result of EC is depicted in figure 7 for three methods. From figure 7, BMC-RLR technique takes lower EC as compared to existing [1] and [2]. This is owing to the application of RAMBC in BMC-RLR technique on the contrary to existing works where it builds strong cluster to groups the sensor nodes into the different clusters based on residual energy. The sensor node with higher residual energy is selected as CH for each cluster. In BMC-RLR technique, CH senses the data concerning target object for accurate object detection in WSN. From that, BMC-RLR technique reduces the amount of energy taken for target discovery as compared to other works. Hence, the proposed BMC-RLR technique minimizes the energy utilization of target detection by 18 % and 28 % when compared to Incremental Clustering-Based Tracking [1] and IM-WSN [2] respectively.

5. LITERATURE SURVEY

A clustering algorithm was designed in [11] for improving moving target tracking accuracy in WSN. Ensemble Support Vector Regression was employed in [12] to find the location of an unknown target in WSN.

Neyman-Pearson discovery method was designed in [13] for performing target detection in a cluster-based WSN with the application of massive multiple-input multiple-output (MIMO) system. With the assist of entropy method, Particle swarm optimization-based energy efficient target tracking was performed in [14].Statistic Experience-based Adaptive One-shot Network (SENet) was designed in [15] to perform target detection in WSN. In [16], Hybrid cluster-based target tracking (HCTT) was introduced for efficient target tracking. A probabilistic detection algorithm was introduced in [17] for discovering target objects using spatiotemporal information in WSN. To find the targets, a prediction-based clustering algorithm was designed in [18].Polygon based target-tracking scheme was designed in [19] to get better energy efficiency and tracking accuracy in WSN. A Dynamic Clustering Algorithm was developed in [20] for detecting the target with higher precision.

6. CONCLUSION

BMC-RLR technique is proposed to improve the performance of target object detection. BMC-RLR technique accurately finds the target node with minimal time with the assist of RLRA as compared to conventional techniques. BMC-RLR technique selects sensor nodes with greater residual energy as CH to predict the target node. From that, BMC-RLR technique achieves enhanced resource-aware data aggregation and target detection performance with a lower time. Simulation analysis of BMC-RLR technique provides enhanced performance in terms of TDA, TDT, EC and ER as compared to conventional works.

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