

Target Tracking Using Radial Distance and Lucas Cluster-Based Ridge Regression in Wireless Sensor Network

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TARGET TRACKING USING RADIAL DISTANCE AND LUCAS CLUSTER-BASED RIDGE REGRESSION IN WIRELESS SENSOR NETWORK

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Abstract

Target tracking is one of the most significant concerns in Wireless Sensor Networks (WSNs). In a densely deployed WSN, spatial trajectories in future mission monitoring can provide comprehensive communication but with dynamically changing network, targets were lost, compromising stability. Some approaches pursue minimum overload and energy consumption occurring during tracking at the cost of tracking accuracy, while some other mechanisms aim to achieve the best tracking accuracy without consideration of energy consumption. In this paper, we present a new method called, Radial Distance and Lucas Cluster-based Ridge Regression (RD-LCRR) to detect and track the target in WSN considering both energy efficiency and accuracy. Initially, we sense the object via Radial Distance Edge Propagation Object Sensing model based on the cluster formation and then identify moving objects through additive value. Next, the object to be tracked is obtained by applying Lucas Kanade Cluster-based Ridge Regression model. Here, target detection is first initialized via Lucas Kanade and finally, the tracking of the actual target is performed through Ridge

Regression. The performance of the RD-LCRR method is considered for different scenarios and experiments are performed in a simulation environment against state-of-the-art methods. Results of the experiments show that the presented target detection and tracking method enables a significant reduction in the amount of energy consumption, target tracking time with higher accuracy rate.

Keywords: Wireless Sensor Network, Target Tracking, Radial Distance, Edge Propagation, Object Sensing, Lucas Kanade, Ridge Regression

1. Introduction

Wireless Sensor Networks (WSN) is a technology attracting more and more distinguished in healthcare, industry at present with innumerable applications and a glaring encouraging future. It necessitates the organization and arrangement of a network in an infrastructure-free environment. Each sensors of the WSN possesses a minute, inexpensive, straightforward to construct and good sensors that will apprehend data pertaining to its environment.

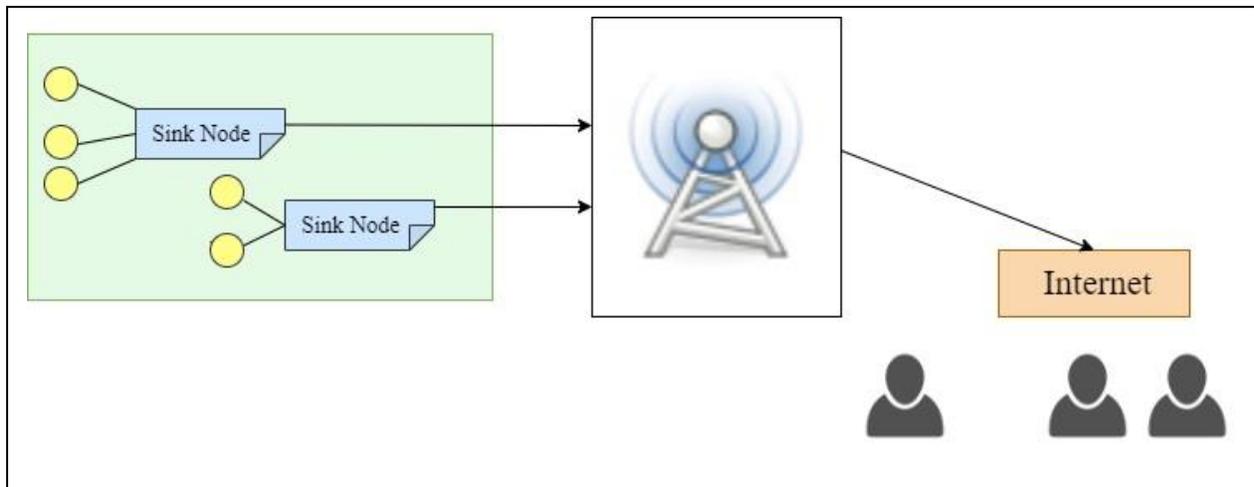


Figure 1 scenario for smart healthcare environment based on IoT

Figure 1 given above illustrates the scenario for smart healthcare environment based on various sensors (i.e. circle with yellow color), sink nodes, base station, internet and users forming WSN. The drastic changes in human body factors negatively impact the health system causing several health issues. These changes are deriving threats to healthcare related aspects in

the developing as well as the developed world. The physiological related challenges that are come across by healthcare sector can be addressed by adopting smart healthcare using IoT devices, which can reduce the mortality of patients.

This article is aimed at utilizing state of the art IoT based sensor framework to acquire medical data from the environment and transfer the data to the cluster head for efficient decisions. In the proposed method, wireless healthcare sensors are used for obtaining different information from the objects or humans. Both the normal information and information with abnormality is intimated to the corresponding cluster head. With this object sensing and also the target tracking via sensors is made in an accurate and timely manner. In this way, the proposed method an energy-efficient and target tracking to automate healthcare sector with minimum human's burden is said to be achieved. The simulated experiments for the proposed method outperformed results when compared to existing methods that are based on different network parameters.

Multiple target tracking in WSN was proposed in [1] with the objective of monitoring and recording data regarding vehicles crossing an area possessing vandalizing environments. In this work, consideration like future mission monitoring was taken into account in addition to the energy consumption involved. Moreover with the assumption that spatial trajectories of the targets being familiar, target speed were also estimated contingent on changeability. With this, multiple targets were able to track at the same time in WSN with better communication between sensors.

Moreover, a linear programming model was utilized with the result being maximization of the overall energy being left. Despite improvement observed with better communication for multiple targets, with the dynamic changing network, targets were lost, compromising the accuracy. To address this issue, a Radial Distance Edge Propagation Object Sensing for WSN is designed that not only forms the cluster based on the energy and power but also sense the objects even in the edge via additive value.

A strategy for target tracking using tube shaped layering and dynamic clustering was presented in [2] with minimum tracking errors. A special type of layering based on tube shaped

was designed that helps routing with no optimization issue by integrating both static and dynamic clustering patterns.

Moreover, an orderly structure was utilized similar to tree to minimize the overload and energy consumption occurring during tracking in WSN. Despite improvement observed in terms of minimizing the overload and energy involved during tracking, however, the accuracy with which the tracking was obtained was not addressed. To provide solution to this problem, in this work, Lucas Kanade Cluster-based Ridge Regression is used for object detection and tracking concentrating on the accuracy and time for tracking.

1.1 Work organization

The rest of this paper is organized as follows. Section 1.2 describes our methodology and contributions. In Section 3, we present a literature of work conducted for target tracking in WSN. In Section 3 the proposed method Radial Distance and Lucas Cluster-based Ridge Regression (RD-LCRR) for target detection and tracking is presented with system model in 3.1, problem statement in 3.2 followed by the elaborated description. Numerical results along with the experimental settings and dataset description are provided in Section 4. The paper is concluded in Section 5.

1.2 Our methodology and contributions

As discussed earlier, the mechanism of multiple targets tracking using the pseudo polynomial algorithm [1] is based only on the continuous coverage of all the targets. In this algorithm, the object sensing in the edges and the dynamic changes were not taken into consideration when electing the master node. As a matter of fact, this may lead to the group formation with some of the objects being sensed as the edges also. The other drawback is the target tracking algorithm used in [2] the accuracy with which target tracking obtained was less focused. In this article, we proposed two new algorithms for optimizing the edge-based clustering and improving target tracking accuracy via machine learning. Our contributions of this article are summarized as follows:

- Proposing energy efficient election model that aims at minimizing the edge-based sensors distance communications between the sensors at different clusters besides electing the cluster head based on the minimum energy and power consumption node for the sake of conserving the network energy and improving target tracking accuracy as well as reducing the target tracking time.
- Proposing an efficient target detection and target tracking model that reduces the number of sensor nodes that participate in the tracking process for the reason of reducing energy consumption in tracking and preserving an equitable tracking accuracy.
- Simulating our algorithms and evaluating their performance utilizing a lot of interesting performance metrics such as energy consumption, target tracking accuracy and target tracking time.

2. Literature review on target tracking

IoT has transformed the world and economy by bestowing absolute association between heterogeneous networks. The ultimate objective of IoT remains in initiating the plug and play strategy administering the end-user, simplicity of functioning, remote monitoring and so on. This paper [3] presented the IoT technology from a bird's eye view providing its architecture, challenges and future advantages. Target tracking remains one of the most popularly used applications of WSN. An Energy-Efficient Filter based Tracking using Kalman Filter was proposed in [4] with the purpose of optimizing the energy being utilized and therefore improving the accuracy of target tracking.

Recent developments in IoT-based wireless communications have resulted in the universal employment of sensor nodes possessing low power. In [5], a new target tracking method in WSN was designed on the basis of an integrated algorithm. The integrated algorithm was the combination of genetic algorithm and Extended Kalman Filter. With this combination not only the energy being consumed was reduced but also positioning precision was improved. However, accomplishing a high tracking accuracy in combination with energy efficiency is found to be exceeding demanding. In [6], two algorithms were designed to improve adaptive

clustering head and prediction model, therefore consuming much less energy in addition to improving the network lifetime.

Applications involving target tracking are very demand in WSN. A method for minimizing energy consumption keeping in mind target tracking was proposed in [7]. However, with higher interference and dynamic topology still target tracking is said to be a challenging issues to be addressed in WSN. A medium access control based on low duty in addition to clustering synchronization procedure was presented in [8]. With this design, communication delay in addition to tracking error were said to be reduced in a significant manner.

Yet another distributed detection and tracking model in WSN was proposed in [9] using consensus based distributed detection and tracking, therefore contributing to accuracy. In addition to Kalman filter, generalized regression model was applied in [10] involving nonlinear dynamic system tracking. IoT applications were presented in [11] to address tracking of COVID-19 patients.

In [12], a robust tracking and localization system was presented by using an energy-efficient Incremental Clustering algorithm with the purpose of tracking the objects at boundary region of static clusters. As a result, both energy consumption and network lifetime were said to be balanced by applying Gaussian Adaptive Resonance Theory (ART) based Incremental Clustering. To ensure smooth target tracking in asynchronous sensors, Time-Difference-Of-Arrival (TDOA) and Frequency-Difference-Of-Arrival (FDOA) was assessed in [13], therefore ensuring smooth trajectory tracking.

A study on data aggregation techniques with respect to target tracking was designed in [14], however the reliability factor was not considered. To address this reliability issue, in [15], Cooperative Localization and Tracking Algorithm (CLTA) were designed using cross grid strategy, aiming at increasing the accuracy of localization.

Target tracking based on virtual grid was designed in [16] to reduce energy consumption and improving network lifetime. Besides energy consumption and network lifetime, one of the

important aspects to be addressed while tracking the target is the coverage. In [17], energy-efficient routing using A-Star algorithm was presented with the objective of improving the network lifetime. However, automatic target tracking was not said to be ensured.

A cooperative sensing model was designed in [18] for tracking the objects in an accurate manner in IoT. In [19], a multi-objective optimization was said to be achieved where scheduling were said to be made for multiple sensor nodes by applying the unscented Kalman filter algorithm. However, boundary detection, losses of data packets and recovery of the lost target are not considered. In [20], extended Kalman Filter was used to achieve tracking mobile targets.

3. Methodology

This section presents the proposed method Radial Distance and Lucas Cluster-based Ridge Regression (RD-LCRR) for target detection and tracking in WSN. Sensors with identifiers (i.e. COVID-19 patients) are used for implementing the tracking. The aim of the RD-LCRR method is to implement a sensing method for tracking mobile objects (i.e. COVID-19 patients) in WSN. Energy consumption, target tracking time and accuracy are criteria that are taken into account in the proposed method. The elaborate description of the proposed method is given below.

3.1 System model

A Wireless Sensor Network comprises of ' n ' numbers of sensors or sensor nodes that are said to be positioned in a consistent pattern with the purpose of monitoring the environment in an uninterrupted manner. Let us represent the ' i th' sensor node ' s_i ' and the respective sensor set ' $V = \{s_1, s_2, \dots, s_n\}$ ' following an IoT pattern, where the sensors in WSN act as the devices. Certain assumptions are made in our work regarding the sensors where each sensor that act as the devices senses the information like, sensor ID, location, timestamp of the entire networks. As far as sensors are concerned, the nodes are positioned in a random manner, with a single base station, with all sensors being homogenous in nature possessing similar potentialities. Also each sensor possesses a unique identifier to differentiate between other sensors during tracking.

3.2 Problem Statement

In the area of target tracking in WSN, the main objective remains in tracking the target that enters cluster and edges, in addition to the target being tracked be obtainable unit it exists the monitoring area subject to energy efficiency and power constraints. The proposed method is based on learning and thus it attempts to track the target via learning. Therefore, when an object enters a monitoring area, the objective remains in tracking the object or target with the least amount of energy consumption and time. On the contrary, it has also to be ensured that the target object is being tracked.

3.3 Radial Distance Edge Propagation Object Sensing

The first step towards target tracking is object sensing. In this work, the object sensing is performed by means of Radial Distance Edge Propagated (RDEP) model. The design of RDEP model involves the measurement of sensing delay and sensing period. The delay from the starting point of the target tracking mission until the time the target tracking result is given back is referred to as the sensing delay. On the other hand, the time between two successive sensing processes is referred to as the sensing period. In order to track the target position in an accurate manner, there require diverse measurements acquired at short time interval. Hence, the sensor nodes or sensors sensing times including sensing delay and sensing period are required to be synchronized for improving target tracking accuracy with minimum time and energy consumption. This is performed in our work by means of RDEP model.

Let us consider that the given monitoring area ' MA ' (i.e., 1400m * 1400m) is positioned in a random manner with ' n ' sensors ' $S = \{s_1, s_2, \dots, s_n\}$ ' that possess the potentiality of assisting comprehensive coverage. Moreover, each sensor ' s_i ' is familiar of its location ' $l_i = (a_i, b_i)$ ' in addition to the edges of ' MA '. The WSN packet comprises of sensor ID, location information ' l_i, l_j ', energy ' E ' and timestamp ' t ' to its neighboring sensors. An efficient energy saving strategy to address the problem of our research is hence required. The energy consumption model used in our work is evaluated by means of the number of idle sensors, number of sensing

sensors and the number of sensors shifting from communicating to sensing. Energy consumption of the node is calculated as given below.

$$EC = \sum_{i=1}^n S_i(E_{Tot}) - [E_{PT} * N_{PT} + E_{PR} + N_{PR} + E_{init}] \quad (1)$$

From the above equation (1), the energy consumption ‘ EC ’, is evaluated on the basis of the total energy of each node ‘ $S_i(E_{Tot})$ ’, energy consumption for packet transmission ‘ E_{PT} ’, energy consumption for packet reception ‘ E_{PR} ’, number of sensors involved in packet transmission ‘ N_{PT} ’, number of sensors involved in packet reception ‘ N_{PR} ’ in addition to the initial energy consumption ‘ E_{init} ’ respectively. Followed by energy consumption, the power consumption is measured as given below.

$$PC = (P_{PT} * t_{PT}) + (P_{PR} * t_{PR}) + (P_{idle} * t_{idle}) \quad (2)$$

From the above equation (2), the power consumption ‘ PC ’ is measured on the basis of the ‘ P_{PT} ’, ‘ P_{PR} ’ and ‘ P_{idle} ’, power consumed in the packet transmission, packet reception and packet idle state and the time duration of sensor being in packet transmission, packet reception and packet idle state ‘ t_{PT} ’, ‘ t_{PR} ’ and ‘ t_{idle} ’ respectively. With the energy consumption and power consumption model, sensors with high energy and power are initiated as the cluster head and the neighboring sensors are said to form a cluster. However, crisis is said to arise when the sensors are positioned in the edges (i.e. circle denoted in red color) and therefore tradeoff occurring with the positioning of sensors as illustrated in the figure 2.

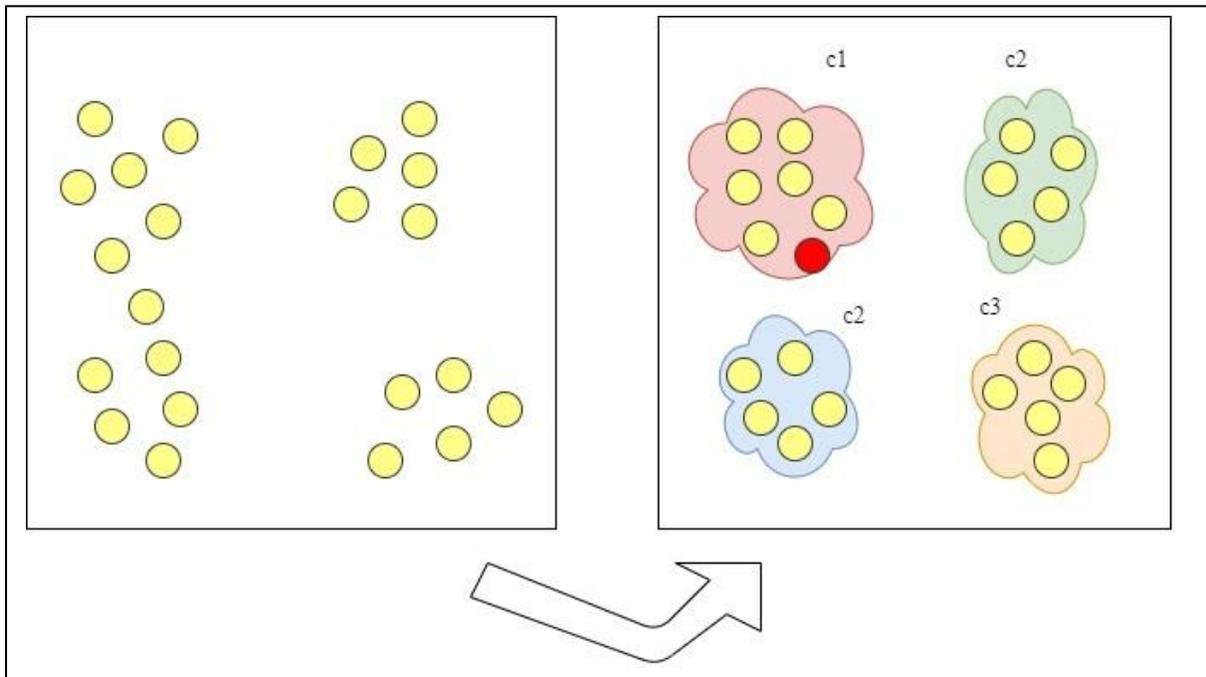


Figure 2 Sample of Edge positioned cluster formation for object sensing

As shown in the above figure, in cluster 1 ' C_1 ', during object sensing and placing the object or sensor in the corresponding cluster, a sensor is said to be detected at the edge resulting in a tradeoff between two clusters ' C_1 ' and ' C_3 ' respectively. To address this issue, in this work object sensing is performed via additive function. Each edge sensor ' ES_i ' evaluates its additive value that is measured by the distance of edge covered by sensor ' S_i '. This additive value ' A_i ' is mathematically formulated as given below.

$$A_i[ES_i] = 2(SR^2 - SD_i^2) \quad (3)$$

From the above equation (3), the additive value of each edge sensor ' ES_i ' is measured based on the sensing radius ' SR ' and the shortest distance ' SD ' between the sensor. With the assumption that the monitoring area (i.e., 1400m * 1400m) is much larger than the sensing area (i.e., 25m * 25m), this ensures that a sensor deployed at the corner of monitoring area ' MA ' divides at most two borders of ' MA '. In this manner, object sensing is said to be performed precisely even in the presence of the sensor in the edges. The pseudo code representation of Radial Distance Edge-based Object Sensing is given below.

Input: Sensors ' $S = s_1, s_2, \dots, s_n$ ', location ' l_i ', energy ' E ' and timestamp ' t '
Output: Energy and power efficient cluster-based object sensing
Step 1: Initialize Monitoring area ' MA ', ' P_{PT} ', ' P_{PR} ' and ' P_{idle} '
Step 2: Initialize ' E_{PT} ', ' E_{PR} ', ' N_{PT} ', ' N_{PR} '
Step 3: Initialize ' t_{PT} ', ' t_{PR} ' and ' t_{idle} '
Step 4: Begin

Step 5: **For** each Sensors ' S ' within Monitoring area ' MA '

Step 6: Obtain energy consumption using equation (1)

Step 7: Evaluate power consumption using equation (2)

Step 8: **For** each edge sensor ' ES_i '

Step 9: Evaluate the additive value using equation (3)

Step 10: **End for**

Step 11: **End for**

Step 12: **Return** (clusters formed ' C_i ')

Step 13: **End**

Algorithm 1 Radial Distance Edge-based Object Sensing

As given in the above Radial Distance Edge-based Object Sensing algorithm, for each sensors with a definite monitoring area, the objective remains in sensing the objects in an energy and power efficient manner even in the presence of sensors in the edge. This is achieved by first dividing the clusters based on the monitoring area and selecting the cluster head in an energy and power efficient manner. Next, object sensing is performed by means of an additive value so that the objects even being sensed in the edges are correctly clustered and therefore laying platform for efficient target tracking.

3.4

Lucas Kanade Cluster-based

Ridge Regression

With the object sensed Radial Distance Edge-based Object Sensing algorithm, the target detection and tracking in WSN is performed by setting referral positions along the network where Clusters are being formed. This cluster is used with machine learning model, Ridge Regression to define a vector-based model, whose input is the clusters and whose output is the corresponding position. To estimate this model, a Lucas Kanade Cluster-based Ridge Regression is used for accurate target detection and tracking. Figure 3 given below shows the block diagram of Lucas Kanade Cluster-based Ridge Regression for target detection and tracking.

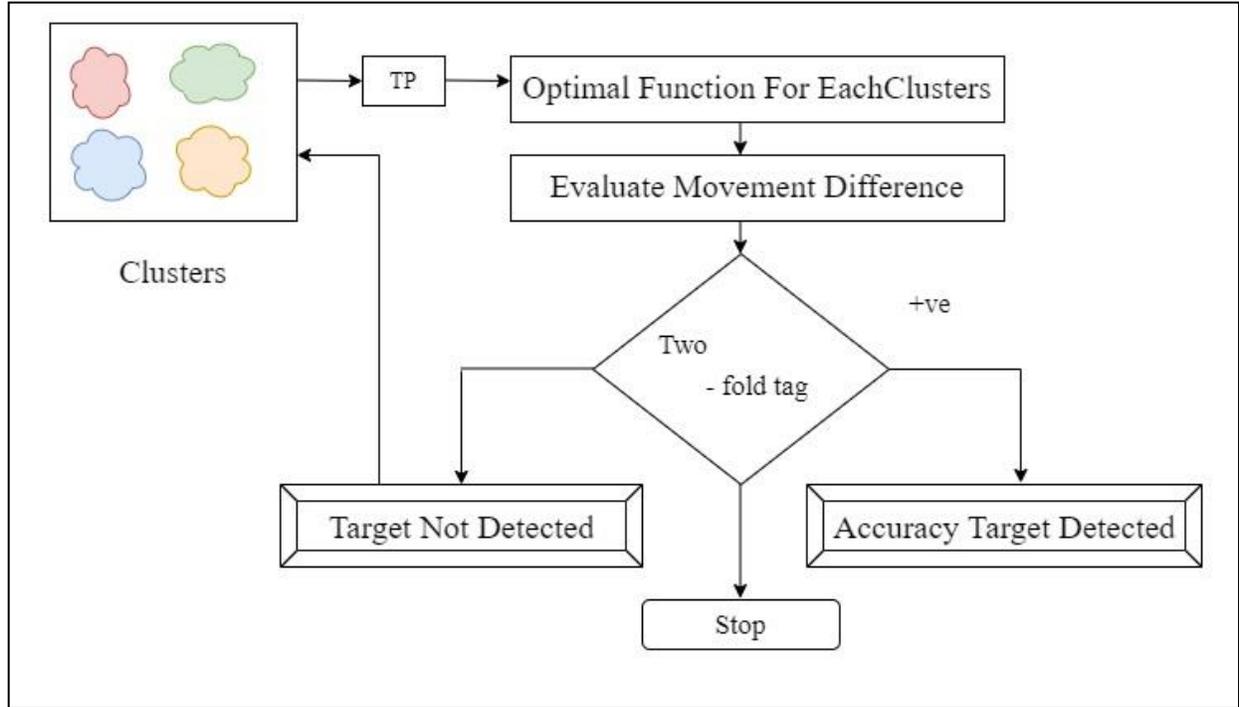


Figure 3 Block diagram of Lucas Kanade Cluster-based Ridge Regression

As illustrated in the above figure, let the vector-valued function ' $V(\cdot)$ ' be split into ' D ' functions, namely ' $V(\cdot) = (v_1(\cdot), v_1(\cdot), \dots, v_D(\cdot))$ ', where ' v_D ' estimates the ' D th coordinate' in ' l_i, l_j ' for an input location ' l_i '. The cluster-based ridge regression is considered to determine the ' D th coordinate', ' $v_1(\cdot), v_1(\cdot), \dots, v_D(\cdot)$ ' by mounting ' D ' disconnected optimization problems. For this, each vector-valued function ' $v_D(\cdot)$ ', is evaluated by cutting down the error between the model's outputs ' $V_D(C_l)$ ' and the desired outputs ' $(C_{l,d})$ '. This is mathematically expressed as given below.

$$\min \frac{1}{S_n} \sum_{l=1}^{S_n} [(C_{l,d} - V_D(l))]^2 + TP (V_D)^2 \quad (4)$$

From the above equation (4), to provide ease in target tracking, with the clusters formed ' C_i ', target tracking is performed in such a manner to first manage the tradeoff between the error and the complexity of the sensed objects. To this, a positive tunable parameter ' TP ' is introduced

so that the tracking is not confined to a particular cluster. Then, the optimal function for a target to be detecting in a cluster is mathematically written as given below.

$$V_D(\cdot) = \sum_{l=1}^{S_n} \beta_{l,d}(C_{l,\cdot}) \quad (5)$$

From the above equation (5), ' $\beta_{l,d}$ where $l \in \{1,2,\dots,S_n\}$ ' are parameters (i.e., sensed objects) to be estimated. Moreover let ' β ' corresponds to the ' $S_n * D$ ' matrix whose ' l,d ' entry is ' $\beta_{l,d}$ '. Next, with the optimal function obtained, a Lucas-Kanade model is applied for target tracking that assumes that all neighboring sensors around the clusters have the same motion. So, the neighborhood motion is measured by formulating the least square problem and is as given below.

$$S_t^{(i,j)} = \operatorname{argmin} [C_{t+1}(S_i + S_{i+1}) - C_t(S_i)]^2 \quad (6)$$

From the above equation (6), the neighborhood motion is arrived at based on the argument of the minimum cluster at ' $t + 1th$ ' timestamp ' C_{t+1} ' and the ' $t th$ ' timestamp ' C_t ' with respect to sensors ' S_i ' and ' S_{i+1} ' respectively. Next, the movement difference ' $Diff_t^n$ ', for detected movement object ' $S_t^{(i,j)}$ ', is mathematically formulated as given below.

$$Diff_t^n = \frac{1}{S_n} \sum_{i,j=1}^{S_n} (R_t^{(i,j)} - S_t^{(i,j)}) \quad (7)$$

From the above equation (7), ' $R^{(i,j)}$ ', corresponds to the movement vector of corresponding sensor from the frame of reference reconstruct between ' S_i ' and ' S_{i+1} ' respectively. Finally, a two-fold tag denoted by ' $Tag_t^{(n)}$ ', is utilized with the positive value denoting that the moving objects at ' $S_t^{(i,j)}$ ', is the target.

$$Tag_t^{(n)} = \begin{cases} 1, & \text{if } Thres \leq Diff_t^n \\ 0, & \text{Otherwise} \end{cases} \quad (8)$$

From the above equation (8), '*Thres*', represent the threshold value set for pruning target tracking. The pseudo code representation of Lucas Kanade Cluster-based Ridge Target Detection and Tracking is given below.

Input: Sensors ' $S = s_1, s_2, \dots, s_n$ ', location ' l_i ', tunable parameter ' TP '
Output: accurate target tracking
<p>Step 1: Initialize clusters formed 'C_i', threshold '<i>Thres</i>'</p> <p>Step 2: Begin</p> <p>Step 3: For each Sensors 'S' within Monitoring area 'MA'</p> <p>Step 4: Obtain vector-valued function with minimum error using equation (4)</p> <p>Step 5: Derive optimal function using equation (5)</p> <p>Step 6: Evaluate neighborhood motion using equation (6)</p> <p>Step 7: Obtain movement difference using equation (7)</p> <p>Step 8: Evaluate two-fold tag using equation (8)</p> <p>Step 9: If '$Tag_t^{(n)} = +ve$'</p> <p>Step 10: Moving object '$S_t^{(i,j)}$', is target</p> <p>Step 11: End if</p> <p>Step 12: If '$Tag_t^{(n)} = -ve$'</p> <p>Step 13: Moving object '$S_t^{(i,j)}$', is not target</p> <p>Step 14: End if</p> <p>Step 15: End for</p> <p>Step 16: End</p>

Algorithm 2 Lucas Kanade Cluster-based Ridge Target Detection and Tracking

As given in the above Lucas Kanade Cluster-based Ridge Target Detection and Tracking algorithm, for each sensed objects in the corresponding cluster as the input, the objective remains in detecting and tracking the target by utilizing machine learning. With this objective, optimal vector valued function is first derived by means of tunable parameter between the models and desired output. Next, movement difference is obtained for detecting the object. Finally, a two-fold tag with the positive value refers to the object being tracked and vice versa.

4. Experiment evaluation

Simulation experiments are performed in order to determine energy consumption, target tracking accuracy and target tracking time for the proposed a method. Energy consumption is evaluated using two criteria: total number of sensors and energy consumed for tracking single sensor. Target tracking accuracy is evaluated by measuring the target being tracked and the overall total number of sensors. Finally, target tracking time is measured based on the total number of sensors and time for tracking. The scope of the experiments incorporates a juxtaposition of the proposed Radial Distance and Lucas Cluster-based Ridge Regression (RD-LCRR) method against existing multiple target tracking in WSN [1] and tube shaped layering and dynamic clustering [2] that have been introduced in the literature for target tracking applications.

4.1 Dataset used

To evaluate the appropriateness of the RD-LCRR method, the method was applied to a benchmark dataset COVID-19 in India dataset obtained from <https://www.kaggle.com/sudalairajkumar/covid19-in-india>. This dataset comprises of information pertaining to the population with respect to age group, details regarding hospital beds made ready for usage of COVID-19 patients, information regarding Indian Council of Medical Research Lab, individual details of the COVID-19 patients, including information like, diagnosed date, age, gender, detected city, detected district, detected state and so on, population details, testing details made in state wise manner obtained from ministry of health and family welfare. Experimental evaluation was carried out on certain factors such as the energy consumption, target tracking accuracy, target tracking time for different number of samples obtained at varied time periods.

4.2 Case scenario

Internet of things (IoT) comprises of diverse elements, like, data collection, data transfer analyses of data and so on. Data collection is performed by sensors via health monitoring devices, then the collected data is sent to a pivotal point for analysis and decision making and accordingly, emergency or ordinary follow up is made forward. In the current scenario, IoT is hitherto utilized in managing certain characteristics of the COVID-19. To name a few instances are, the usage of drones for public citizen inspection to make certain quarantine and the wearing of masks. IoT can also be utilized in making certain patient consent once the probably contaminated or infected persons become part of quarantine.

By severe tracking of the object (i.e., infected persons) health personnel can easily monitor the patients remaining quarantined and the patients breaching the quarantine. In this work, a case scenario of target tracking is performed with COVID-19 patients. Here, the target refers to the COVID-19 patients and by tracking the target, the patient history regarding his visit, his contacts are obtained with which isolation or quarantine is in regulation. With the details pertaining to COVID-19 patients obtained via the sensors and sent to the base station, accordingly cluster head with minimum energy and power consumption along with the clusters are said to be formed. With the formation of cluster, easy tracking of objects or targets (i.e., COVID-19 patients) are made.

4.3 Simulation setup

Based on the experimental setup and as provided in table, the monitored area is a square of 1400 * 1400 meters. During the process of simulation, a single target moves in a random manner within the actual monitored area. The simulated WSN includes 500 sensor nodes that are positioned in a square grid framework. Each sensor node in the network performs detection and target localization in a sensing area of 25 * 25 meters. Transmission range of each sensor node covers the eight nearest neighboring nodes. Comprehensive information on focal parameters of the simulation is incorporated in Table. The simulation environment was based on NS2 simulator.

Table 1 Parameters of simulation

S. No	Parameter	Description
1	Monitored area	1400m * 1400m
2	Sensor node transmission range	40m
3	Sensor node sensing area	25m * 25m
4	Bandwidth	250 kbits/sec
5	Packet size	56 bytes
6	Number of nodes	500
7	Mobility model	Random way point

4.3.1 Performance measure of energy consumption

A significant amount of energy is said to be consumed during the tracking of target in WSN. Hence, energy consumption for target tracking in WSN is considered to be a vital element. The mathematical representation of energy consumption is given below.

$$EC_{TT} = \sum_{i=1}^n S_i * EC \quad (9)$$

From the above equation (9), the energy consumption for target tracking ' EC_{TT} ' is measured based on the number of sensors considered for simulation ' S_i ' and the energy consumption ' EC ' measured from equation (1). It is measured in terms of joules 'J'. Table 2 summarizes the energy consumption of individual sensor nodes. From the average energy consumption provided in the table, we can predict that the experiment with 50 nodes has the lowest energy being consumed 0.0015J compared to two other methods.

Table 2 Energy consumption using RD-LCRR, Multiple target tracking in WSN [2] and Tube shaped layering and dynamic clustering [2]

Sensor nodes	Energy consumption (J)		
	RD-LCRR	Multiple target tracking in WSN	Tube shaped layering and dynamic clustering

50	0.0015	0.002	0.0025
100	0.0022	0.003	0.0035
150	0.0024	0.0055	0.006
200	0.0027	0.0065	0.008
250	0.0035	0.007	0.0085
300	0.0049	0.0085	0.009
350	0.0052	0.009	0.0094
400	0.0055	0.0095	0.0097
450	0.007	0.0098	0.0105
500	0.0074	0.0099	0.0125

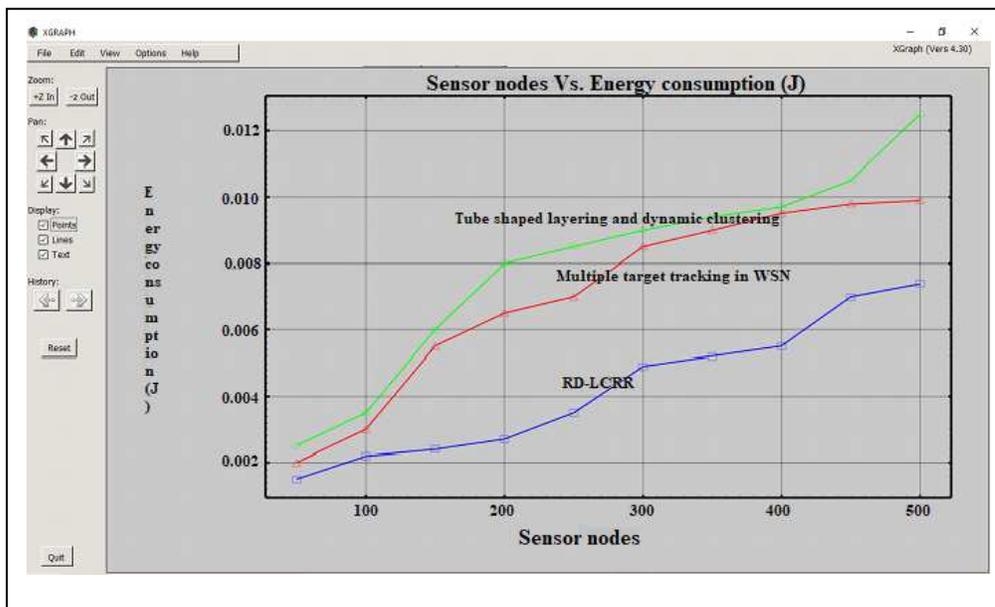


Figure 4 given above illustrates the energy consumption with respect to different numbers of sensor nodes in the range of 50 to 500. From the figure it is inferred that increasing the sensor nodes increases the objects or targets to be tracked and obviously results in the increase in the energy being consumed for target tracking. Simulations conducted with 50 sensors found to be 0.0015J of energy being consumed using RD-LCRR, 0.0020J of energy being consumed using [1] and 0.0025J consumed using [2]. From this simulation results it is inferred that the energy consumption using RD-LCRR is found to be comparatively lesser than the existing methods. The reason for the improvement is the application of Radial Distance Edge-based Object Sensing

algorithm. By applying this algorithm, first cluster was formed to sense the object based on the energy consumption in addition to the power being consumed and according the cluster was said to be formed. Moreover, by applying additive function, edge-based object sensing was done in a significant manner, therefore reducing the energy consumption for target tracking using RD-LCRR method by 40% compared to [1] and 12% compared to [2] respectively.

4.3.2 Performance measure of target tracking time

In addition to the energy consumed during tracking a portion of time is also said to be consumed during target tracking in WSN. Faster the target tracking time earlier is the identification of the target and therefore efficient is the method said to be. The target tracking time is mathematically formulated as given below.

$$Time_{TT} = \sum_{i=1}^n S_i * Time [Diff_t^n] \quad (10)$$

From the above equation (10), the target tracking time ' $Time_{TT}$ ' is measured based on the number of sensors for simulation ' S_i ' and the time consumed in obtaining movement difference ' $Time [Diff_t^n]$ ', with which the target tracking is made. It is measured in terms of milliseconds (ms). Table 3 summarizes the target tracking time of individual experiments. From the average target tracking time provided in the table, we can predict that the experiment with 50 nodes has the lowest target tracking time of 1.25ms compared to two other methods. As small number of sensors are scattered throughout the WSN network and the average vary a lot compared with the large number of sensors, the tracking time is higher for experiments with fewer nodes than for higher nodes.

Table 3 Target tracking time using RD-LCRR, Multiple target tracking in WSN [2] and Tube shaped layering and dynamic clustering [2]

Sensor nodes	Target tracking time (ms)		
	RD-LCRR	Multiple target tracking in WSN	Tube shaped layering and dynamic clustering
50	1.25	2.1	2.5

100	1.85	2.35	3.25
150	2.35	3.15	4.85
200	4.15	5.25	6.26
250	4.85	6.1	8
300	5.25	7	9.15
350	6	7.25	10
400	6.35	8	11.25
450	6.85	8.35	13
500	7.25	9	14.15

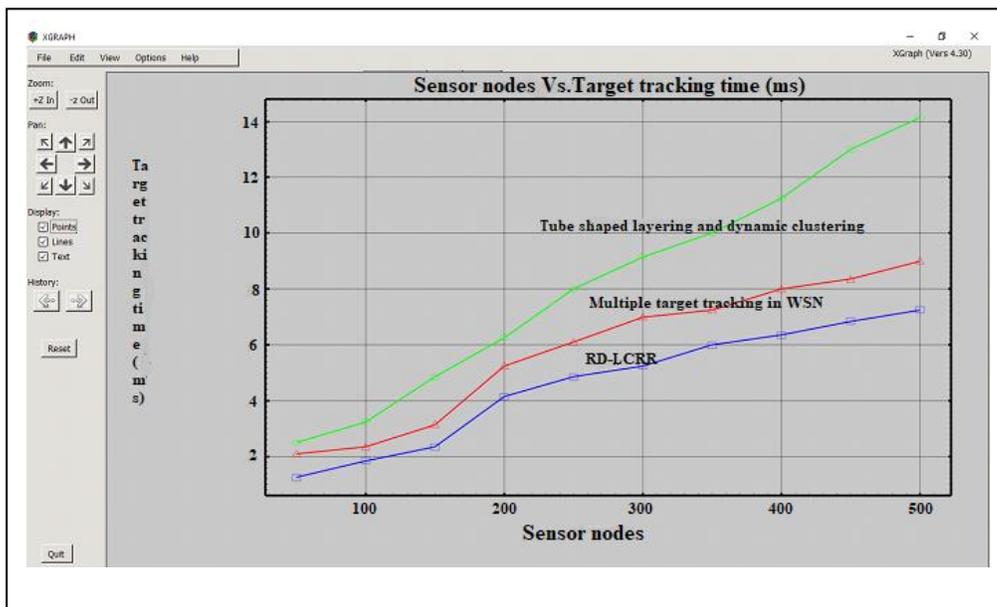


Figure 5 Graphical representation of target tracking time

Figure 5 given above shows the target tracking time with respect to 500 numbers of sensor nodes. With x axis representing the sensor nodes and y axis representing the target tracking time, both are said to be directly proportion to each other. This is because of the reason that increasing the number of sensor nodes increases the time taken to form cluster and therefore the target tracking time also increases. From the figure it is inferred with simulations conducted for 50 sensors, the target tracking time was observed to be 1.25ms, 2.1ms and 2.5ms using RD-LCRR, [1] and [2] respectively. The reason being the improvement is the application of Cluster-

based Ridge Regression in the Lucas Kanade Cluster-based Ridge Target Detection and Tracking algorithm. With this, the error between the modeled outputs and desired outputs is said to be considerable reduced, therefore arriving optimality for a target to be detected in cluster. Hence, the target tracking time using RD-LCRR is said to be reduced by 23% compared to [1] and 44% compared to [2] respectively.

4.3.3 Performance measure of target tracking accuracy

Finally, the target tracking accuracy is measured as given below.

$$Acc_{TT} = \sum_{i=1}^n \frac{TT_c}{S_i} * 100 \quad (11)$$

From the above equation (11), the target tracking accuracy ‘ Acc_{TT} ’, is measured based on the sensors utilized for simulation purpose ‘ S_i ’ and the target being tracked correctly ‘ TT_c ’. It is measured in terms of percentage (%). Table 4 summarizes the target tracking accuracy of individual experiments.

Table 4 Target tracking accuracy using RD-LCRR, Multiple target tracking in WSN [2] and Tube shaped layering and dynamic clustering [2]

Sensor nodes	Target tracking accuracy (%)		
	RD-LCRR	Multiple target tracking in WSN	Tube shaped layering and dynamic clustering
50	94	90	88
100	92.15	89.1	87.45
150	91.85	88.35	86
200	90	88	86.35
250	90	88	86
300	91.35	89.35	88.15
350	91.55	90	89.25
400	89.25	88.15	87.15

450	90.35	89.35	88
500	93.15	90.25	88.35

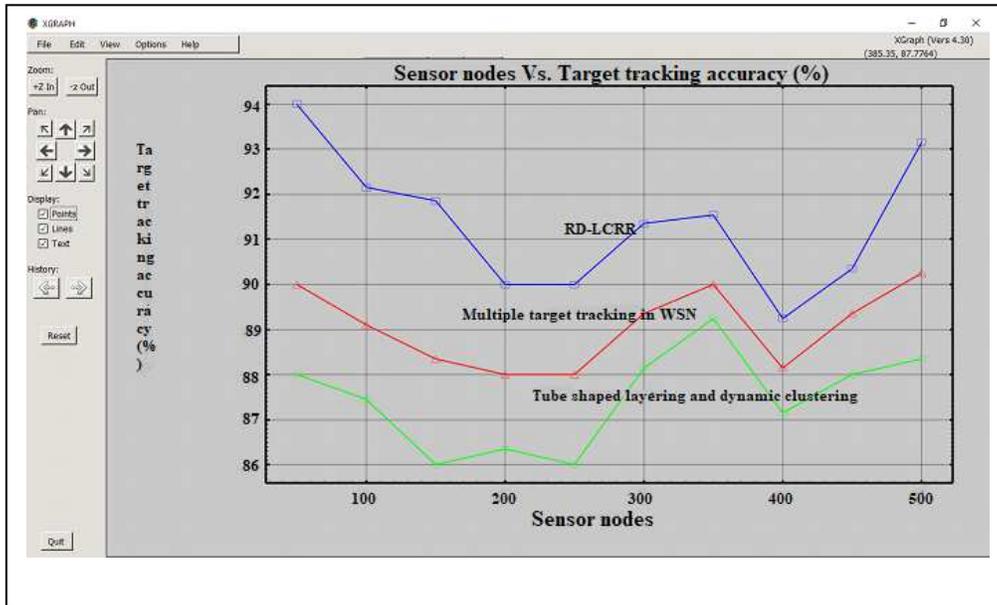


Figure 6 Graphical representation of target tracking accuracy

Finally, figure 6 given above illustrates the target tracking accuracy with respect to different sensors collected at different time intervals. From the figure it is inferred that the target tracking accuracy neither increases nor decreases with the increase in the number of sensor nodes. The reason behind is with high changing topology in WSN the positioning of the target object to be detected also changes its position in a dynamic manner. Therefore the accuracy also increases or decreases with the increase in the number of sensor nodes. However, simulations conducted with 50 sensors saw an accuracy of about 94% using RD-LCRR, 90% using [1] and 88% using [2] respectively. The improvement is due to the application of Lucas-Kanade where same movement is said to be found between all neighboring sensors around the clusters. With this, the objects are tracked accurately using RD-LCRR by 3% compared to [1] and 4% compared to [2] respectively.

5. Conclusion

The automation of WSN accomplishes an indispensable part in the evolution of the healthcare domain. This paper presents an energy-efficient target tracking IoT based WSN framework for smart healthcare application. The main aim of the proposed method is to designate the more appropriate additive decision function. The decision is based on residual energy, power consumption and the edge object sensing factors. Moreover, the proposed method is to appropriate a machine learning technique along with a neighborhood movement evaluation model for accurate target detection and decreases the prospects of restrictions among healthcare sensors (i.e., in our case considering COVID-19 patients as target to be detected). Our proposed method presents an intelligent Lucas Kanade Cluster-based Ridge Target Detection and Tracking algorithm for accurate target detection and minimizes the ratio of ratio of energy consumption with improved detection in the healthcare field. Moreover, the proposed method offers accurate target tracking with minimum time from healthcare sensors based on movement vector of corresponding sensor from the frame of reference. The simulation results demonstrate the energy efficiency with higher target tracking accuracy in minimum time.

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