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# Energy-Efficient Tracking and Localization of Objects in Wireless Sensor Networks

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**ABSTRACT** The energy-efficient tracking and precise localization of continuous objects have long been key issues in research on wireless sensor networks (WSNs). Among various techniques, significant results are reported from applying a clustering-based object tracking technique, which benefits the energy-efficient and stable network in large-scale WSNs. As of now, during the consideration of large-scale WSNs, a continuous object is tracked by using a static clustering-based approach. However, due to the restriction of global information sharing among static clusters, tracking at the boundary region is a challenging issue. This paper presents a complete tracking and localization algorithm in WSNs. Considering the limitation of static clusters, an energy-efficient incremental clustering algorithm followed by Gaussian adaptive resonance theory is proposed at the boundary region. The proposed research is allowed to learn, create, update, and retain clusters incrementally through online learning to adapt to incessant motion patterns. Finally, the Trilateration algorithm is applied for the precise localization of dynamic objects throughout the sensor network. The performance of the proposed system is evaluated through simulation results, demonstrating its energy-efficient tracking and stable network.

**INDEX TERMS** Object tracking, wireless sensor network, incremental clustering, trilateration, adaptive resonance theory.

## I. INTRODUCTION

As of now, the advanced communication technology in the miniaturization and integration of diverse heterogeneous sensing units offering low cost and low power has led to future ultra-large networks. In regard to their environmental monitoring, surveillance, and automated data collection, sensor networks and their potential applications are highly appreciated in both commercial places and the military nowadays [1]. Tracking moving objects throughout an established network has gained popularity due to its basis for many potential applications such as forest fires, mud flows, oil spills [2], gas leakage in large-scale petrochemical plants [3], preserving wild species [4], emergency rescue [5], [6], patient monitoring [7], [8], and battlefield surveillance [9]. Location flexibility, cost effectiveness, and stable networks are the key features for the rising popularity of continuous object tracking recently. However, energy-efficient tracking and stable networks are still being researched and enhanced.

Specifically, the task of tracking involves two consecutive steps [10]. The detection of the object presence throughout the network and location calculation are in the first step. Tracking or monitoring the continuous moving object is in the second step. In spite of diverse task capability, a sensor node also has limitations. Sensor nodes are mainly battery-operated, and hence they have a limited lifetime. Therefore, the challenging issue for each Wireless Sensor Network (WSN) is raising energy efficiency performance while reducing radio communication as well as computation cost.

### A. THE WSN TRACKING AND LOCALIZATION PROBLEM

A WSN is a collection of sensor nodes formed as a cluster-based organization. Initially, bounded area sensor nodes are close together based on the sensing range to track moving objects inside some static clusters [11]. Energy efficiency is the specific aim for this cluster-based architecture in large-scale WSNs. However, information sharing globally is prohibited for static clusters. In this regard, the task of tracking may get lost at the boundary region of each static cluster. To address this issue properly, an accurate boundary shape [12] is calculated firstly and then Dynamic Clustering [10] is applied to create and dismiss on-demand basis cluster when an object enters and exits the boundary region of each static cluster. However, the frequent creation and deletion of clusters may consume vast energy due to the inability of retaining clusters, even recently created ones. Moreover, erroneous distance-based location estimation may reduce the reliability score of continuous object localization.

### *B. OBJECTIVE OF THE RESEARCH*

As can be observed from the discussion of Section 1.1, existing methods are facing the challenges of energy consumption, faulty tracking, and inaccurate localization. Hence, mitigating the aforementioned issues is the primary objective of the proposed research. In this vein, this research is focused on incremental clustering-based moving object tracking and Trilateration-based localization [13]. Sensor nodes in an incrementally formed cluster are allowed to share an object's update information with static clusters. It is very important for online learning to consider the stability/plasticity dilemma [14], i.e., how a system is able to learn new node patterns and update without defiling existing patterns. In this regard, incremental clustering is very efficient to learn, update, and retain clusters. Fig. 1 visualizes a general tracking route (dotted red line) on which an object (a car) moves. The tracking sequence among different clusters (both static and incrementally created) throughout the network is also directed in this figure.

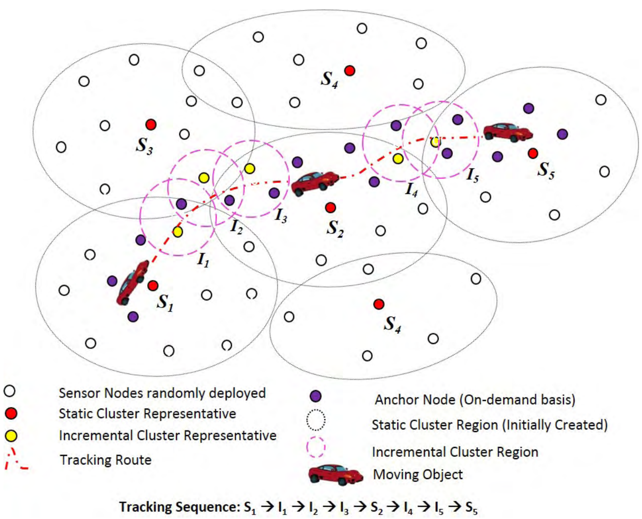



**FIGURE 1. Visualization of a car tracking throughout a network in the proposed research.**

First, the car is tracked by the static cluster S1 until it reaches the boundary region of S1. For the smooth continuation of the tracking task, the I1, I2, and I3 clusters are created on an on-demand basis by applying the Incremental Clustering algorithm at the boundary region of the initially created static clusters. While the car is passing from the S2 cluster to the S5 cluster, clusters I4 and I5 are created incrementally. In this way, the car is tracked from S1 to S5 with the sequence: S1 → I1 → I2 → I3 → S2 → I4 → I5 → S5. The proposed research also calculates the anchor nodes to estimate the precise 2D location of the car by applying the Trilateration-based algorithm. In regard to anchor node selection, signal strength analysis using the Received Signal Strength Indicator (RSSI) is proposed.

The principal contribution of this research is to propose a robust tracking and localization system for WSNs. In addition, an energy-efficient Incremental Clustering algorithm is proposed to track objects at the boundary region of static clusters towards achieving the aforementioned objectives. The performance of the proposed tracking accuracy and network lifetime is examined and presented here by using a simulation, demonstrating the significance of the proposed research.

The research paper is organized as follows. Section 2 describes the thorough background of object tracking in WSNs. In Section 3, addressing the boundary tracking problem with a possible solution space is discussed. This section also reviews the proposed system. In Section 4, a complete tracking and localization algorithm is presented. This section also explains the Incremental Clustering algorithm based on Gaussian Adaptive Resonance Theory (ART) with proper mathematical equations. In Section 5, the performance of the proposed research is evaluated in a simulation environment. Eventually, a concluding remark with possible future scope is highlighted in Section 6.

## II. LITERATURE REVIEW

Due to its importance for application domains in the sensor community, the object tracking and localization technique has attracted the interest of many researchers [15], [52]. Existing research on object tracking techniques and algorithms can be visualized in the taxonomy [16] shown in Fig. 2.

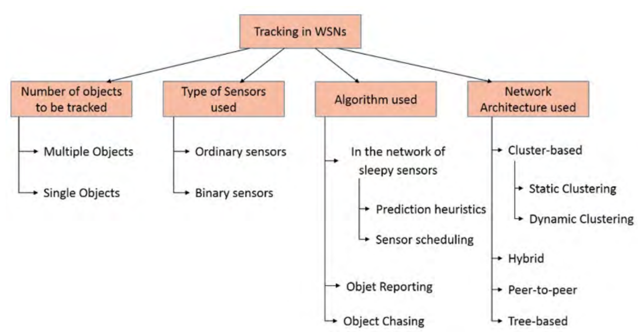



**FIGURE 2. Object tracking taxonomy.**

### A. TRACKING STRATEGIES

Based on the network architecture, object tracking algorithms are mainly categorized as tree-based, cluster-based, hybrid-based, prediction-based, and model-based. A hierarchical tree in the network represents a tree-based architecture such as Optimized Communication and Organization [17], Scalable Tracking Using Networked Sensors (STUN) [18], and Dynamic Convoy Tree based Collaboration (DCTC) [19]. Based on the Euclidean distance between two sensor nodes, STUN calculates a cost function to build a network grid. Furthermore, the previously calculated cost function is used to construct a logical tree without reflecting the physical arrangement of the sensor network. However, the DCTC algorithm focuses on dynamic tree construction for moving object tracking. In [20], a dynamic power-level sensing topology is proposed for location estimation in WSNs.

An information-driven dynamic sensor collaboration mechanism was presented by Zhao *et al.* [21]. Brooks *et al.* [22] focused on a framework of distributed entity tracking for sensor nodes. In [23], a three-step distributed target tracking technique was presented in wireless video sensor networks. Vigilnet [24], [25] designed an energy-efficient technique to support real-time object tracking in WSNs. Moving object monitoring in ultrasonic sensor networks is focused on applying the Time Division Multiple Accesses [26] method, providing a distributed nature. To defend existing networks against common attacks, [27] presented a secure location-aware algorithm. A fuzzy-based test bed system [28] was proposed and evaluated to detect an actuator with low latency and proper task assignment for target tracking in Wireless Sensor and Actuator Networks.

In regard to sensor collaboration with an energy-efficient mechanism, dynamic clustering-based algorithms are proposed. Among them, Yang *et al.* [29] presented an Adaptive Dynamic Cluster-based Tracking protocol to select on-demand basis cluster heads. Wake up nodes and clusters form through a prediction-based algorithm during object moving throughout the network. Rad *et al.* [30] and Islam [31] researched the balance between energy consumption and the missing rate through his dynamic clustering mechanism. Medeiros *et al.* [32] implemented an efficient dynamic clustering algorithm to work on camera networks for object tracking. Considering the holes phenomenon with a data structure, a Continuous Object Detection and tracking [33] algorithm was proposed to reduce the communication cost in WSNs.

Examples of prediction-based movement analysis and further object location detection techniques are DPT (Distributed Predicted Tracking), the Markov Additive Chain Model [34], DPR (Dual Prediction-based Reporting) [35], trajectory tree construction [36], the Improved Mining Pattern [37], and the Node Activation Mechanism [53]. The aim of individual prediction-based architecture is to keep most of the sensor nodes in a sleeping state to provide an energy-efficient mechanism. Advancing a one-to-one connection to a one-to-many connection between a sink and many sources, namely a sink mobility scheme [38], was proposed to track moving objects in WSNs. In recent years, WSNs have been composed of a set of static clusters [39]–[41] of a group of sensor nodes based on their sensing range. Examples of these types of protocols include Low Energy Adaptive Clustering Hierarchy (LEACH) [11] and HEED [42] followed by the cluster structure of sensor nodes. By using hierarchical levels for static and dynamic clusters, [43] tracked objects in quantized areas of WSNs. Rad *et al.* [30] proposed an Adaptive Prediction-based Tracking scheme that provides energy efficiency while focusing on lowering the missing probability.

Current research focuses on clustering-based object tracking in WSNs, such as the Smart-cluster Continuous Object tracking Protocol [2], two agent-based approach [44], Incremental Clustering-based Facial Feature Tracking [51], and Hybrid Clustering-based Target Tracking (HCTT) [10]. HCTT creates and dismisses on-demand basis dynamic clusters when an object enters and exits the boundary of a static cluster. In [45], a boundary recognition and tracking algorithm for continuous objects was proposed to ensure the efficiency of object contour extraction. However, these protocols consume more energy due to frequent cluster formation and deletion. In any case, HCTT cannot retain clusters, even recently created ones. In this regard, the proposed system highlighted by the Incremental Clustering algorithm [46] can learn the upcoming node pattern through online learning, cluster them, and retain frequently formed clusters without defiling the existing cluster. When the proposed system experiences a new node pattern, it is able to calculate the best matching pattern among existing clusters. If no such cluster is found, a new cluster will be formed with an upcoming pattern; otherwise, the cluster will update. In this way, an energy-efficient tracking process continues throughout the network.

### B. LOCALIZATION STRATEGIES

On the contrary, obtainable localization techniques are divided into two types: range-free [56] and range-based techniques. Range-based techniques assume the relative directions of neighbors and/or the absolute distance calculation. Examples of such techniques include the following: LOcalization and Tracking (eLOT) [47], RSSI [13], Time Of Arrival (TOA) [16], Peak Signal to Noise Ratio (PSNR) [1], Time Difference Of Arrival (TDOA) [15], Hybrid Localization [54], and Progressive Isomap [55]. Among them, N-hop-multilateration [12] and Euclidean [2] are the most representative algorithms. To quantify the geometric relationship of objects, [1] proposed the Quality of Trilateration (QoT). Wang [48] presented a precise location estimation method using object tracking techniques in WSNs. Based on three anchor nodes, an apex of a weighted polygon is calculated to estimate the position through an Alternating Combination Trilateration (ACT) [45] algorithm. However, distance-based localization sometimes is unreliable due to an inaccurate reported distance. In this research, both RSSIs based on the power strength analysis for anchor node formation are considered. Finally, the 2D position of the selected anchor nodes will allow the accurate localization of a moving object.

## III. PROBLEM FORMULATION

In regard to the robust tracking in WSNs, we first investigate the specific problem of continuous object tracking based on a literature review. Then, we propose an efficient energy-saving technique to address that problem for our research. The operation of the Incremental Clustering algorithm is discussed later.

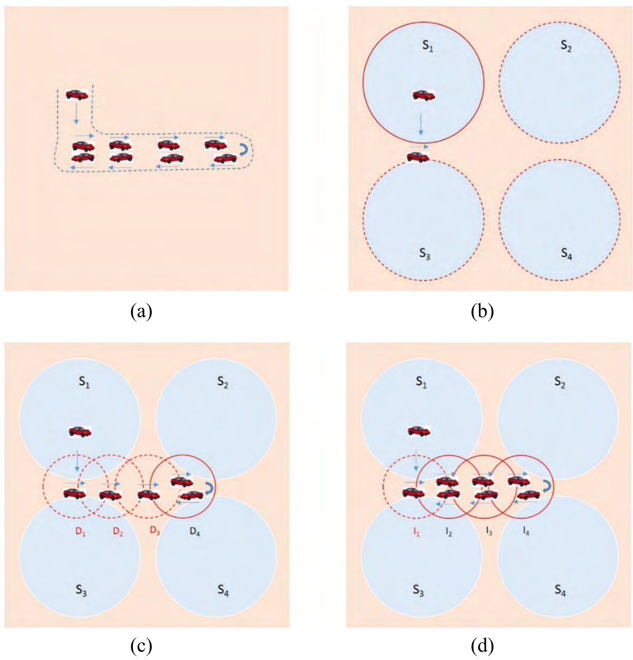



**FIGURE 3. Visualization of boundary problem. (a) General tracking sequence, (b) Tracking limitation of static clusters, (c) Boundary tracking through dynamic clusters, and (d) Energy efficient incremental clustering.**

### A. BOUNDARY PROBLEM

In recent research, sensor nodes are grouped together and clustered into some static clusters based on the sensing range for the smooth continuation of the tracking task, which further ensures a low-cost and energy-efficient solution. Fig. 3(a) shows the boundary problem visualization during object tracking on the already visited path. Each cluster is represented as a circular shape, while active and dismissed clusters are denoted by solid lines and dashed lines, respectively. Fig. 3(b) shows four initially formed static clusters to continue car tracking. When the car is located inside the range of any static cluster, a representative of that cluster is responsible for monitoring that car; at that time, other sensor nodes of the remaining clusters go into sleeping mode and free from communication. However, due to the restriction of sharing global information among static clusters, the task of tracking might be misleading at the boundary. Hence, only the S1 cluster can track when the car is inside the boundary region of S1. Due to the prediction error, the tracking task can fail when the car is at the boundary of S1.

In this vein, to continue the tracking task at the boundary region, dynamic clusters [2] are proposed to create an on-demand basis. While the object is present in any dynamic cluster, sensor nodes surrounded by that cluster are allowed to share information temporarily. The existing cluster will be dismissed once the object has left that cluster and another one will be formed. In spite of efficient collaboration among sensor nodes, dynamic clustering suffers too many overheads due to frequent cluster formation and deletion, which consumes more energy. Fig. 3(c) shows the frequent cluster formation and deletion when an object revisits the visited path. Cluster D4 is responsible for tracking the car when it presents in that cluster, whereas clusters D3, D2, and D1 are re-created if the car is considered to revisit the tracking route.

### B. SOLUTION SPACE

To address the aforementioned issues, an Incremental Clustering algorithm at the boundary region is proposed in this subsection. Frequent clusters are also retained in the system to ensure energy efficiency tracking. A new cluster will be created if the observation pattern does not match the existing cluster of node patterns; otherwise, the cluster will be allowed to update. Fig. 3(d) visualizes on-demand basis cluster formation (incrementally) at the boundary region during tracking. The significance of the proposed system is easily understood by the clusters I4, I3, and I2 during object tracking on the revisited path. However, the I1 cluster is created once only and then dismissed due to both space and computational complexity. Therefore, only the I1 cluster has to be created twice if an object wants to revisit the visited track, which signifies the proposed system.

### C. OVERVIEW OF THE PROPOSED SYSTEM

The fundamental problem addressed in this research work is tracking in the boundary region and localizing the moving object throughout a network over time. Fig. 4 outlines the overview of the proposed research in four major stages as follows:

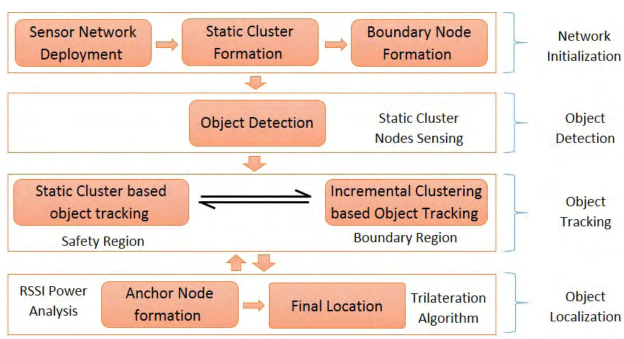



**FIGURE 4. Overview of the proposed research.**

#### 1) NETWORK INITIALIZATION

The first step of each WSN is to initialize the network by deploying the sensor nodes throughout. In this step, the proposed research follows the LEACH protocol to organize the sensor nodes into clusters. The LEACH protocol includes two main features: distributed cluster formation and energy efficiency. The cluster building procedure is adaptive, which is very efficient in large-scale WSNs. Each static cluster is defined with geographically close nodes within a predefined communication range headed by a cluster representative. Boundary nodes are responsible for monitoring the objects in a boundary region. This research work focuses on an existing boundary node formation algorithm [10] to calculate the boundary nodes of each static cluster. Sensor nodes are location-aware and share local information with their neighbors. At the end of this step, a set of boundary nodes from each static cluster is formed based on the communication range of each node.

#### 2) OBJECT DETECTION

Once a sensor network is initialized, the sink node takes control of the object detection through the cluster representatives. Based on the sensing range, the cluster representative will notify the sink about the object presence in the corresponding cluster. The sink node will then turn on all the sensor nodes of that cluster to keep tracking the object and keep turn off the other cluster's nodes for energy efficiency.

#### 3) OBJECT TRACKING

Based on the communication range of each sensor node, the representative is aware of the presence of the object. Until receiving a response from the boundary nodes, the task of tracking is continued by the static cluster representative. Whenever, the representative acknowledges the object's approximate location in the boundary region, it will create clusters incrementally in the boundary region. Incremental clustering firstly learns from the environment about the node pattern and observation pattern, and it then creates clusters to keep tracking the object. Finally, it retains the recent cluster for energy saving purposes. If the observation pattern is not matched with the previously created clusters, a new cluster will be created to continue tracking in the boundary region.

#### 4) OBJECT LOCALIZATION

Finally, based on the RSSI power strength analysis, the cluster representative will select three nodes as anchor nodes. At the end of this step, by applying the Trilateration algorithm on the anchor nodes, the object's current position in 2D space is calculated accurately.

## IV. INCREMENTAL CLUSTERING-BASED TRACKING

Clustering-based object tracking in WSNs has better accuracy nowadays. However, dynamic clustering-based tracking is an energy consuming and cost-effective technique. Due to the frequent formation and deletion of dynamic clusters rather than retaining them, network lifetime is falling. In this vein, a combination of object tracking techniques, namely static clustering-based tracking inside static clusters and incremental clustering-based tracking at the boundary, is proposed to ensure an energy-efficient and low-cost solution.

### A. ROBUST TRACKING AND LOCALIZATION ALGORITHM

The aim of the proposed research is to address boundary localization, energy consumption, and object localization. Algorithm 1 describes a complete algorithm for robust tracking and localization in WSNs to optimize the aforementioned issues in some sense. The proposed algorithm is an integration of consecutive steps: sensor node deployment and initialization, incremental clustering-based tracking, and the Trilateration-based localization of continuous objects in WSNs.

**Algorithm 1** Robust Tracking and Localization in WSNs

**Requires:**
Network Initialization,Static Cluster Formation and Representative Selection,Observation Pattern
**Ensures:**
*Robust Tracking and Localization thoughout the Network*

1: *Formation of Static Cluster and network initialization*
2: *Formation of Boundary*
3: ***while*** *(detect object)* ***do***
4: ***if*** *object located in safety region* ***then***
5: *Representative of Static is Responsible for Tracking*
6: ***else*** *(object located in boundary region)*
7: ***if*** *Observation Pattern fulfil the Membership Condition of Incrementally Created Clusters* ***then***
8: *Update Mean, Covariance, Count and Weight of Incrementally Created Clusters*
9: ***else***
10: *Create a new Cluster using Incremental Clustering Algorithm* ***(Algorithm 2)***
11: *Representative of Incrementally Created Cluster Responsible for Tracking*
12: ***end if***
13: ***end if***
14: *Anchor Node Selection from Winner Cluster applying RSSI-based Analysis*
15: *Object Localization applying Trilateration Algorithm* ***(Algorithm 3)***
16: ***end while***

### B. INCREMENTAL CLUSTERING-BASED OBJECT TRACKING

Cluster-based object tracking can capture object's different movements throughout the network benefiting stable and energy efficient network. The whole tracking task defined in Algorithm 2 is composed of two consecutive steps. Firstly, the representative of static cluster will monitor object's precise location during object detects inside the boundary of static cluster. Secondly, the representative of

**Algorithm 2** Incremental Clustering-Based Object Tracking

**Requires:**

*Set of n Clusters*, $PC = \{PC_1, PC_2, \ldots\ldots, PC_n\}$ *with Mean as Representatives*, $\{\mu_1, \mu_2, \ldots\ldots, \mu_n\}$,
*Covariance*, $\{\sum_1, \sum_2, \ldots\ldots, \sum_n\}$,
*Weights* $\{w_1, w_2, \ldots\ldots, w_n\}$,
*Baseline Vigilance Parameter*, $\rho$
*Initial Covariance Matrix*, $\sum_0$
*Maximum Number Of Components*, $Comp_{MAX}$
*Maximum Number Of Clusters*, $PC_{MAX}$
*and a Test Pattern/Obsevation Pattern*, $O_p$

**Ensures:**

*Incremental Clustering: Updated/New Cluster*

**for** all $PC_i$ **do**
  *Calcualte Activation* $(Act_i)$ *using Eq.* (10)
  *Calcualte Winner Cluster* $(k \leftarrow Max\,(Act_i)\,, k = 1, 2, \ldots, n)$ *using Eq.* (11)
  *Calcualte Vigilance* $\left(Vigil_k\right)$ *using Eq.* (12)
  **if** $Vigil_k \geq \rho$ **and** $\left|Comp_{kj}\right| \leq Comp_{MAX}$ **then**
    *UpdateMean* $(\mu_k)$ *as in Eq.*(13)
    *UpdateCovariance* $\left(\sum_k\right)$ *as in Eq.*(14)
    *UpdateWeights* $(w_k)$ *as in Eq.*(7)
  **else**
    *UpdateWeights* $(w_1, w_2, \ldots\ldots, w_n)$ *as in Eq.* (7)
    **if** $|PC_i| = PC_{MAX}$ **then**
      Find $PC_m|w_m \leq w_i m = 1, 2, \ldots\ldots n$
      $PC_i \leftarrow PC_i \backslash PC_m$
      $PC_m \leftarrow O_p$
      $\mu_m \leftarrow O_p$
      $\sum_m \leftarrow \sum_0$
      $w_m \leftarrow 0$
      $Comp_{mj} \leftarrow 1$
    **else**
      $PC_{i+1} \leftarrow O_p$
      $\mu_{i+1} \leftarrow O_p$
      $\sum_{i+1} \leftarrow \sum_0$
      $w_{i+1} \leftarrow 0$
      $Comp_{i+1j} \leftarrow 1$
    **end if**
  **end if**
**end for**

on-demand basis created incremental cluster will monitor the tracking task during object detects at the boundary region of any static cluster using proposed Incremental Clustering Algorithm incorporating with Gaussian Adaptive Resonance Theory (GART) [46], [49]. Due to capability of online learning, clustering, updating, and retaining frequently used clusters (patterns), Incremental Clustering has gaining its popularity now-a-day. Because of sensors are deployed in 2D space, they are considered to follow the Gaussian distribution.

In point distribution space, similar pattern of sensor nodes are closed together to form a group or cluster representing tracking pattern, away from other sensor nodes representing dissimilar patterns. The mean pattern is the representative of each cluster. Individual Cluster is defined by covariance matrix $\sum_i$, mean vector $\mu_i$, and a weight value $w_i$. The number (count) of cluster member at any time in the network is denoted by $n_i$. For initializing the tracking network two parameters such as: initial covariance matrix $\sum_0$ and baseline vigilance parameter $\rho$ are required. Network performance improvement is significantly depends on choosing proper values for aforementioned parameters.

The activation value calculation for individual cluster is fully depends on the conditional density of an observation pattern $O_p$ followed by Eq. (1):

$$p\left(O_p|i\right) = \frac{1}{(2\pi)^{M/2}\left|\sum_i\right|^{1/2}} \exp \times \left[-\frac{1}{2}\left(O_p - \mu_i\right)^T \sum\nolimits_i^{-1}\left(O_p - \mu_i\right)\right] \quad (1)$$

where $M$ represents the dimensionality of the input patterns.

Eq. (2) denotes the winner cluster with the highest activation value, which represents the highest probability of a cluster matching with the observation pattern.

$$K = \arg\max_i p\left(O_p|i\right) \quad (2)$$

However, the winner cluster is allowed to update only if it satisfies the vigilance condition according to Eq. (3).

$$Exp\left[-\frac{1}{2}\left(O_p - \mu_N\right)^T \sum\nolimits_K^{-1}\left(O_p - \mu_K\right)\right] \geq \rho \quad (3)$$

Based on satisfying Eq. (3), the mean, covariance, count, and weight of the winner cluster are allowed to update according to Eqs. (4–7); otherwise, the cluster will lose weights according to Eq. (7).

$$Comp_k = Comp_k + 1 \quad (4)$$

$$\mu_K = \left(1 - \frac{1}{Comp_k}\right)\mu_K + \left(\frac{1}{Comp_k}\right)O_p \quad (5)$$

$$\sum_K = \left(1 - \frac{1}{Comp_k}\right)\sum_K + \left(\frac{1}{Comp_k}\right)(O_p - \mu_K)(O_p - \mu_K)^T \quad (6)$$

$$w_K^{(t+1)} = \begin{cases} (w_K^{(t)} + \alpha)\dfrac{1}{1+\alpha} & \text{if } K = \text{index of updated Cluster} \\ w_K^{(t)}\dfrac{1}{1+\alpha} & \text{Otherwise} \end{cases} \quad (7)$$

In any case, if no such cluster is selected as the winner cluster to update, a new cluster will be created with only one element i.e., observation pattern $O_p$ with weight $w_K^{(t+1)} = 0$ and count $Comp_k = 0$. To limit the memory requirement as well as computational complexity, a particular number of clusters will be retained in the network by removing the lowest weighted cluster. By applying Gaussian ART algorithms, clusters will create and grow incrementally without defiling the existing clusters in an energy-efficient way.

### C. C. TRILATERATION-BASED LOCALIZATION

Once the object has been found to belong to a cluster, the cluster representative will select three anchor nodes based on the RSSI analysis. The 2D position of the anchor nodes will be used to estimate the object's current position by using the Trilateration algorithm as shown in Algorithm 3. By using range-based information, the Trilateration algorithm calculates the spheres in the 3D space and returns the object's 2D location accurately.

A sphere is created by the range between the unknown node and a reference node. If the range information is accurate, the different spheres intersect, resulting in one solution. The basic formula for the general sphere is shown in Eq. (8).

$$\begin{aligned} D_{in} &= \sqrt{(X_i - X_n)^2 + (Y_i - Y_n)^2} \\ D_{in}^2 &= (X_i - X_n)^2 + (Y_i - Y_n)^2 \end{aligned} \tag{8}$$

Since all the nodes span out on the same plane, consider the three anchor nodes (1, 2, 3) that have a distance ($D_{1n}$, $D_{2n}$, $D_{3n}$) to the blind node ($X_n$, $Y_n$) as shown in Fig. 5. After substituting and rearranging the location of the object from the three anchor nodes as in Eq. (9).

$$\begin{aligned} X_n &= \frac{D_{1n}^2 - D_{2n}^2 + X_2^2}{2X_2} \\ Y_n &= \frac{D_{1n}^2 - D_{3n}^2 + X_3^2 + Y_3^2 - 2X_n X_3}{2Y_3} \end{aligned} \tag{9}$$

**Algorithm 3** Trilateration-Based Object Localization

**Requires:**
Anchor Node $N_i = \{(X_i, X_i)\}, i = 1, 2, 3.$
**Ensures:**
Object Location $(X_n, Y_n)$
1. ***for** all $N_i$ **do***
2. *Calculate Sphere Using Eq. (9)*
3. *Solve the non-linear equations by rearranging and subtracting*
4. *Calculate the Coordinate of Object Location {Using Eq. (13) - (14)}*
5. ***end for***

## V. SIMULATION AND PERFORMANCE EVALUATION

Through the proposed ongoing research, static clustering performance is significant in object tracking. Further, the research focuses on implementing all the proposed algorithms described in the previous section.

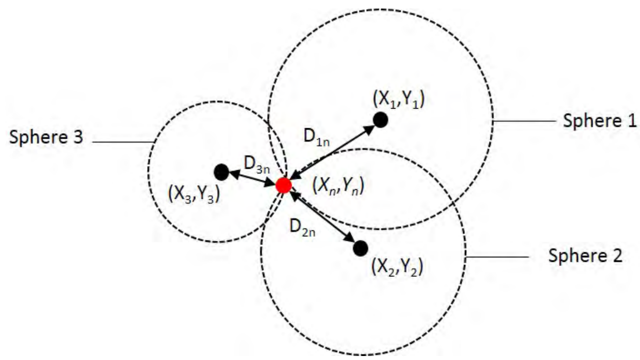



FIGURE 5. Intersect location of three spheres in 2D.

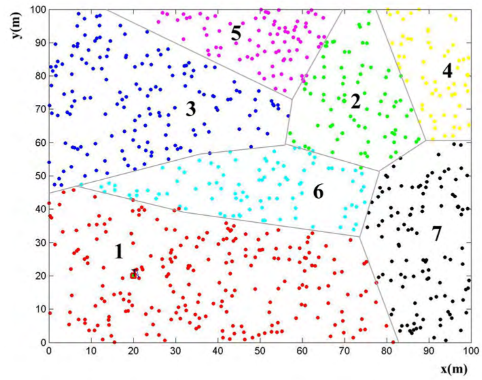


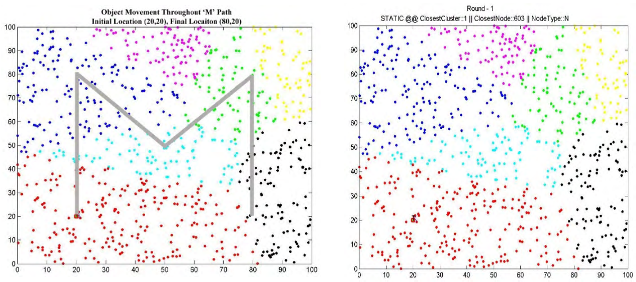

FIGURE 6. Random deployment of sensor nodes in the WSN.

### A. ENVIRONMENTAL SETUP

We carry out a simulation by using a Matlab simulator with different combinations of sensor nodes randomly deployed in an area of $100 \times 100\ m^2$ for continuous object tracking, as shown in Fig. 6. The proposed system considers three sets of experiments with various sensor nodes to demonstrate wide accuracy: experiment #1 with 400 nodes, experiment #2 with 600 nodes, and experiment #3 with 800 nodes. During transmit and receive, the proposed system is considered to be an application of radio transmission of energy dissipation. The radio dissipation rate to operate the receiver or transmitter circuitry is assumed to be *50 nJ/bit* and the amplifying rate for the transmit amplifier is assumed to be *100 pJ/bit/m*$^2$ to achieve an acceptable ratio [10]. In regard to the channel transmission, at most $r^2$ energy can be lost [50]. In this sense, for transmitting a k-bit message in the long run, a significant number of sensor nodes will go down. For performance comparison, we have used various parameters such as tracking sequence analysis, tracking accuracy and network lifetime analysis throughput tracking, which are explained in the following sections. For performance comparison, we have used various parameters such as tracking sequence analysis, tracking accuracy and network lifetime analysis throughput tracking, which are explained in the following sections.

### B. EXPERIMENTAL RESULT OBSERVATION

Fig. 6 visualizes a sample simulation result of the random deployment of 800 nodes in a $100 \times 100$ m$^2$ area, where the object (indicated by the rectangular box with the 'T' character symbol) will start its journey from the (20,20) position of the 2D coordinate system. Initially, we create seven static clusters by using the static clustering (the LEACH protocol) algorithm. The nodes of specific clusters are identified by suitable colors. The big node of each cluster is defined as the cluster head. The object will move throughout the network to draw an 'M' path until 4500 rounds to complete its journey. The purpose of this research is to track the object on the 'M' path by using incremental clustering with the static clustering algorithm. Once the object is detected within the sensing range of a set of nodes, the cluster head forms anchor nodes (three points of a triangular shape in Fig. 5.2 and successive figures) and estimates the correct location by using the Trilateration algorithm. In regard to the tracking accuracy comparison, the proposed system also experiments and compares the results with dynamic clustering.




(a) (b)

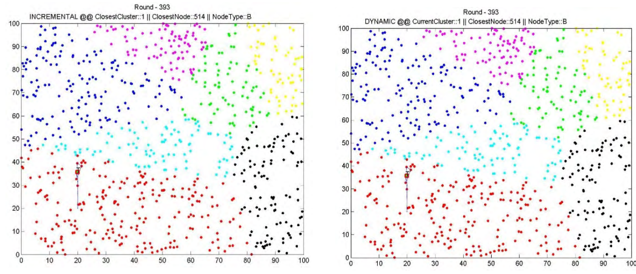
**FIGURE 7.** Object tracking visualization.

## C. TRACKING SEQUENCE ANALYSIS

Fig. 7 indicates the first round of the tracking process where the object is detected by the first static cluster. The closest node number to the object is 603 and the type of node is normal (denoted by 'N'). During tracking, once the object is sensed by the boundary node (node type denoted by 'B'), the proposed system will automatically create clusters based on the Incremental Clustering algorithm at the boundary region of the static cluster to continue the tracking process.

Through simulation, we can observe that when the object is moving towards the boundary region of static cluster 1, incremental clustering is formed to continue the tracking task. At round 393, the first incremental cluster is formed as the closest node (node number 514) to the object in the boundary nodes of static cluster 1. For considering dynamic clustering, the first dynamic cluster is formed at the same round, as shown in Fig. 8.

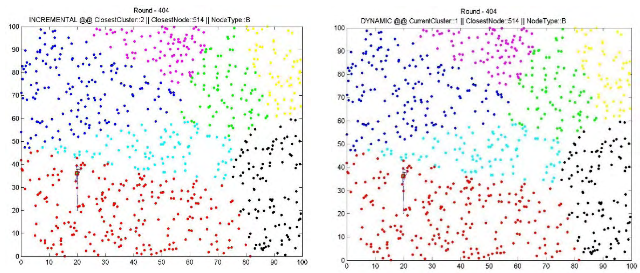
When an object passes through the boundary region, a number of clusters are created incrementally by incorporating the boundary nodes of the in-between static clusters. Among the nodes, we consider the three closer nodes to the object as an observation pattern, while the closest node is represented as the cluster head. Incremental clustering is considered to be a Gaussian distribution of sensor nodes followed by mean and covariance. Based on the vigilance criterion, existing clusters will be updated or a




(a) (b)

**FIGURE 8.** Cluster formation at the boundary region at round 393. (a) First incremental cluster. (b) First dynamic cluster.

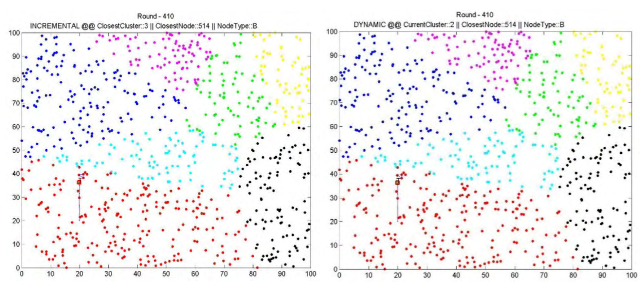
new cluster will be created, as per our previous discussion (in Section 4.2.2). Whereas in the case of dynamic clustering, when a new node pattern is experienced, it will create a new cluster and dismiss the previously created one.




(a) (b)

**FIGURE 9.** Incremental cluster formation observation. (a) Second incremental cluster. (b) Dynamic cluster unchanged.

In Fig. 9(a), although the observation pattern is the same, a second incremental cluster is created as the existing (first) incremental cluster is unable to fulfil the vigilance criteria due to the frequently updated mean and covariance since 11 rounds. Fig. 9(b) indicates that the number of dynamic clusters is still the same; the node pattern is also similar. To reduce the computational cost, we will keep the same number of incremental clusters as in the static cluster. The cluster with the lowest weight will be replaced with the new cluster when the number of clusters reaches its maximum value.




(a) (b)

**FIGURE 10.** Cluster formation due to new observation pattern encountered. (a) Third incremental cluster. (b) Second dynamic cluster.

During object tracking at the boundary region, if the observation pattern is completely different, both clustering algorithms create a new cluster, as shown in Fig. 10. Once an object moves from the previously created cluster, incremental clustering updates its existing clusters, whereas dynamic clustering dismisses the previously created cluster. The process of cluster formation and deletion increases the number overheating, which further consumes more energy in the network. Eventually, nodes tend to lose their energy and die in the long run.

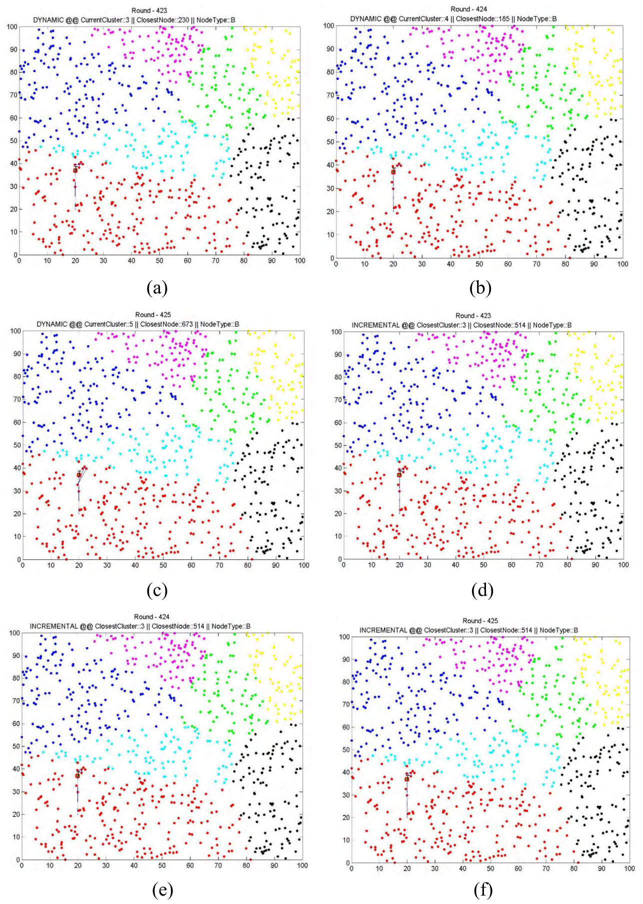



**FIGURE 11.** **Frequent dynamic cluster formation due to increasing number of dead node. (a) Third dynamic cluster. (b) Fourth dynamic cluster. (c) Fifth dynamic cluster. (d) Incremental cluster unchanged. (e) Incremental cluster unchanged. (f) Incremental cluster unchanged.**

Figs. 11(a), (b), and (c) show how frequently dynamic clustering is created due to decreasing alive nodes in the boundary regions to track the object. Figs. 11(d), (e), and (f) show for the same rounds that the number of incremental clusters is the same as before as clusters are considered to be updated only.

Incremental clustering updates the mean and covariance of existing clusters. Hence, if a similar observation pattern is encountered in the network, it is expected that the existing cluster can satisfy the vigilance criterion and update the cluster with that pattern. Fig. 12 shows two consecutive rounds (498–499 and 3635–3636) where a similar node pattern is predicted to track the object and the number of incremental clusters remains the same as before. The simulation results also provide the efficient tracking and localization inside the region of static clusters. Fig. 13 depicts static clustering-based

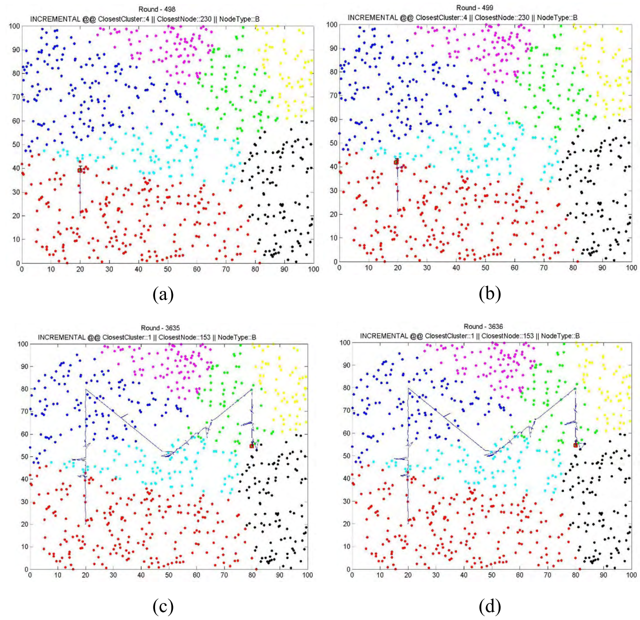



**FIGURE 12.** **Significant of the incremental clustering algorithm. (a) Similar pattern observation at round 499. (b) Similar pattern observation at round 498. (c) Similar pattern observation at round 3636. (d) Similar pattern observation at round 3635.**

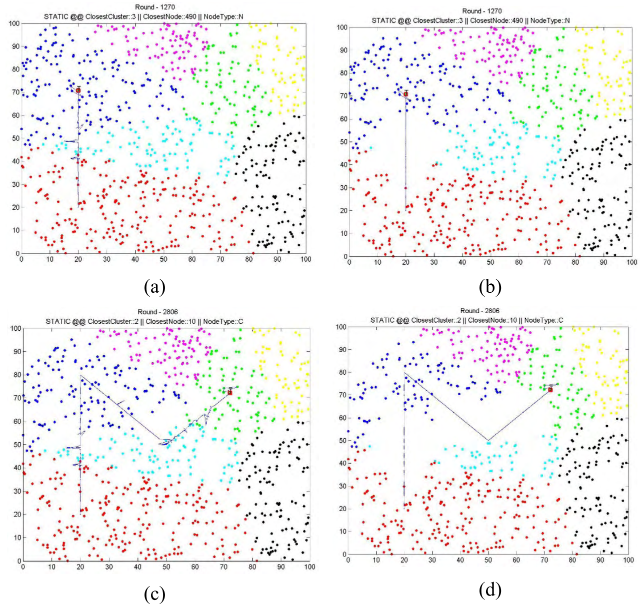



**FIGURE 13.** **Static clustering-based object tracking in parallel with incremental clustering and dynamic clustering. (a) With incremental clustering at round 1270. (b) With dynamic clustering at round 1270. (c) With incremental clustering at round 2806. d) With dynamic clustering at round 2806.**

tracking and localization in parallel with incremental clustering and dynamic clustering. Here, we see that the proposed clustering provide efficient result.

#### 1) NETWORK LIFETIME ANALYSIS THROUGHOUT TRACKING

Fig. 14 shows the visited 'M'-path of the object during tracking throughout the network with different clustering algorithms. Dynamic clustering can provide smooth

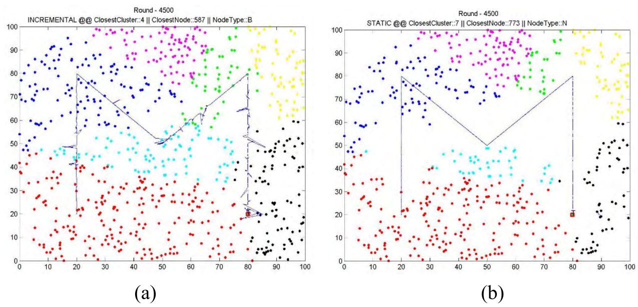



**FIGURE 14.** Complete tracking on 'M'-path with clustering algorithms. (a) Incremental clustering. (b) Dynamic clustering

tracking, while incremental clustering suffers from a few tracking errors. On the contrary, incremental clustering is outperformed for network lifetime, reducing the number of dead nodes compared with dynamic clustering.

### D. ACCURACY OF THE SIMULATION RESULTS

In this paper, we conducted three sets of experiments to track the object throughout the 'M'-path. Each set of experiments contains 10 observations. Each observation has randomly deployed sensor nodes over the network followed by 4500 rounds to complete the 'M'-path tracking. The numbers of sensor nodes for each set of experiments are 400, 600, and 800, respectively.

#### 1) TRACKING ACCURACY ANALYSIS

The criteria for calculating tracking accuracy is to compute the distance of the predicted coordinate by using clustering algorithms compared with the manually labelled ground truth coordinate [20], [52]. The average error is given as:

$$m_e = \frac{1}{nS} \sum_{i=1}^{i=n} d_i \tag{10}$$

$$d_i = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{11}$$

where n denotes the number of sensor nodes initially considered throughout the network, S represents the Euclidean distance between a pair of reference points (in our case, the start and end position of the 'M'-path tracker), and $d_i$ is the Euclidean point to the point errors for each individual location of an object.

**TABLE 1.** Average tracking error calculation for 3 set of experiments.

| | Experiment #1: 400 Sensor Nodes | | Experiment #2: 600 Sensor Nodes | | Experiment #3: 800 Sensor Nodes | |
|---|---|---|---|---|---|---|
| Observation | IC | DC | IC | DC | IC | DC |
| 1 | 0.01265 | 0.00125 | 0.24991 | 0.00083 | 0.01577 | 0.00063 |
| 2 | 0.02026 | 0.00125 | 0.24991 | 0.00083 | 0.00715 | 0.00063 |
| 3 | 0.01725 | 0.00125 | 0.02532 | 0.00083 | 0.03286 | 0.00063 |
| 4 | 0.01398 | 0.00125 | 0.04470 | 0.00083 | 0.04049 | 0.00063 |
| 5 | 0.01487 | 0.00125 | 0.01956 | 0.00083 | 0.03489 | 0.00063 |
| 6 | 0.01310 | 0.00125 | 0.01436 | 0.00084 | 0.12379 | 0.00063 |
| 7 | 0.00466 | 0.00125 | 0.01132 | 0.00083 | 0.01183 | 0.00063 |
| 8 | 0.01290 | 0.00125 | 0.01793 | 0.00084 | 0.02638 | 0.00003 |
| 9 | 0.67734 | 0.00125 | 0.02496 | 0.00083 | 0.02835 | 0.00063 |
| 10 | 0.57283 | 0.00125 | 0.02312 | 0.00083 | 0.03068 | 0.00063 |
| Average | 0.13598 | 0.00125 | 0.06811 | 0.00084 | 0.03522 | 0.00057 |
| **Error (%)** | **13.6** | **0.13** | **6.81** | **0.08** | **3.52** | **0.06** |

*IC=Incremental Clustering, DC= Dynamic Clustering*

Table 1 summarizes the tracking error of individual experiments. From the average error provided in the table, we can predict that the experiment with 800 nodes has the lowest tracking error of 3.52% and 0.06% for the incremental and dynamic clustering algorithms, respectively. As small number of nodes scattered throughout the network and the mean and covariance will vary a lot compared with the consolidated network (e.g., a large number of nodes). Hence, the predicted tracking error is higher for experiments with fewer nodes for tracking with incremental clustering. Although dynamic clustering provides better tracking accuracy than incremental clustering, it consumes more energy as described in the following section.

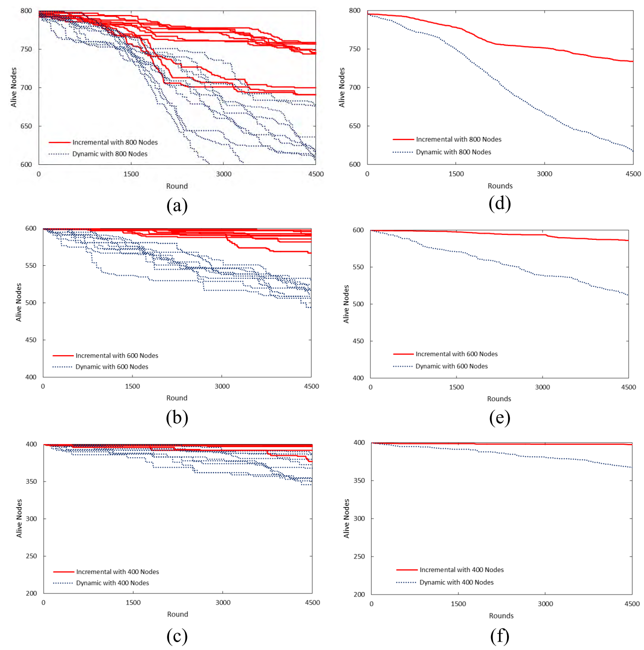



**FIGURE 15.** Round vs. Alive node observation applying incremental and dynamic clustering on distinct set of experiments. (a) Round vs. Alive nodes for experiment #3. (b) Round vs. Alive nodes for experiment #2. (c) Round vs. Alive nodes for experiment #1. (d) Average Round vs. Alive nodes for experiment #3. (e) Average round vs. Alive nodes for experiment #2. (f) Average round vs. Alive nodes for experiment #1.

#### 2) NETWORK LIFETIME ANALYSIS

Network lifetime can be measured through the number of alive nodes per round (time) during object tracking throughout the network. Figs. 15(a), (b), and (c) show the number of alive nodes per round for 10 observations of each set of experiments, using both incremental clustering and dynamic clustering. The results visualize that incremental clustering is more energy-efficient as the number of dead nodes is less compared with dynamic clustering. Figs. 15(d), (e), and (f) visualize the average number of alive nodes per round (time) for each set of experiments. It is clearly visible that incremental clustering more than doubles the network lifetime compared with dynamic clustering. By applying the dynamic clustering technique, the number of dead nodes increases due to frequent cluster creation and dismisses during object tracking.

In Fig. 16, the cumulative distribution of dead nodes for 4500 rounds to track the object in the predefined 'M'-path

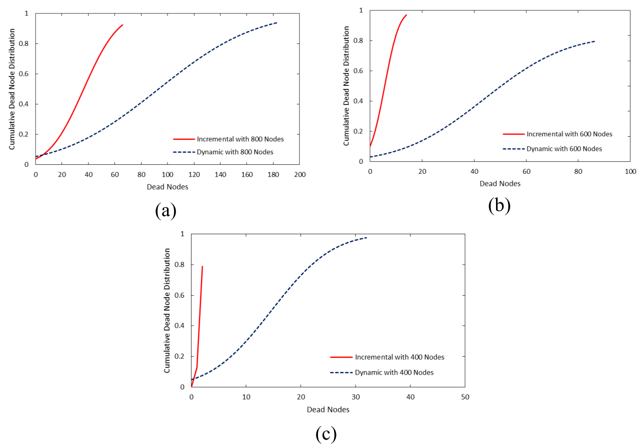



**FIGURE 16. Cumulative Dead Node Distribution over 4500 Rounds of distinct set of experiments. (a) Cumulative distribution of Dead nodes for experiment #3. (b) Cumulative distribution of dead nodes for experiment #2. (c) Cumulative distribution of dead nodes for experiment #1.**

for each set of experiments is shown. Considering 800 nodes, incremental clustering is more energy-efficient than dynamic clustering for object tracking with the number of dead nodes <60 in 90% of cases compared with 30% of cases for dynamic clustering, as shown in Fig. 16(a). Fig. 16(b) shows that considering 600 nodes, incremental clustering is more energy-efficient than dynamic clustering with the number of dead nodes <15 in 95% of cases compared with 10% of cases for dynamic clustering. Fig. 16(c) shows that considering a simulation with 400 nodes, incremental clustering is more energy-efficient than dynamic clustering with the number of dead nodes <5 in 80% of cases compared with 5% of cases for dynamic clustering. Therefore, incremental clustering is more stable and energy-efficient that dynamic clustering.

## VI. CONCLUSIONS

We developed a continuous object tracking and localization system through the online learning of dynamic tracking patterns. To balance energy consumption and network lifetime, the system proposed a Gaussian ART-based Incremental Clustering algorithm that aggregates the new sensor node pattern as observed, clusters them based on sensing ranges, and finally organizes the acquired information in an efficient growing and self-organizing manner without defiling the previously learned node patterns. Due to the restriction of sharing global information for static clusters, incremental clusters are created at the boundary of static clusters on a demand basis to continue object tracking throughout the network. The simulation results demonstrate the energy efficiency and stable network provided by the proposed system. In our future work, we plan to enlarge the network size with real-time implementation to support tracking both indoors and outdoors. In addition, we will investigate the privacy and security aspect of the tracking to enhance the proposed idea.

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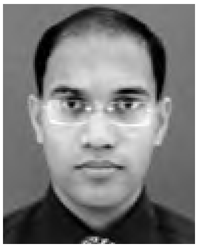

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