Incremental Clustering-based Object Tracking in Wireless Sensor Networks

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***Abstract*— Emerging significance of moving object tracking has been actively pursued in the Wireless Sensor Network (WSN) community for the past decade. As a consequence, a number of methods from different angle of assessment have been developed while relatively satisfying performance. Amongst those, clustering based object tracking has shown significant results, which in term provides the network to be scalable and energy efficient for large-scale WSNs. As of now, static cluster based object tracking is the most common approach for large-scale WSN. However, as static clusters are restricted to share information globally, tracking can be lost at the boundary region of static clusters. In this paper, an Incremental Clustering Algorithm is proposed in conjunction with Static Clustering Technique to track an object consistently throughout the network solving boundary problem. The proposed research follows a Gaussian Adaptive Resonance Theory (GART) based Incremental Clustering that creates and updates clusters incrementally to incorporate incessant motion pattern without defiling the previously learned clusters. The objective of this research is to continue tracking at the boundary region in an energy-efficient way as well as to ensure robust and consistent object tracking throughout the network. The network lifetime performance metric has shown significant improvements for Incremental Static Clustering at the boundary regions than that of existing clustering techniques.**

***Keywords*—Object Tracking, Wireless Sensor Networks (WSN), Incremental Clustering, Energy-efficiency, Adaptive Resonance Theory.**

I. INTRODUCTION

Recent advancement in the miniaturization and integration of low-cost, low-power sensing units and communication technologies have led many ultra-large networks. With their capability for automated data collection, surveillance, and environmental monitoring, Wireless Sensor Networks (WSNs) and their applications have remarkable prospective in both military and commercial places. Tracking objects throughout the established network is one of the most concerned areas in WSNs. Object tracking in WSNs has gained a lot of popularity for many empirical applications, such as battlefield surveillance, emergency rescue, patient monitoring and preserving wild species [1]. Cost effectiveness, location flexibility, and long-lifetime of networks are the most important features and challenges for object tracking applications. However, achieving robustness and energy efficiency in tracking are still being researched and improved.

In general, object tracking in WSNs involves two steps [2]. Firstly, sensor nodes need to detect the presence of a moving object within an area of interest, estimate its location, and forward the location information to the base station. Secondly, it needs to control the tracking process to monitor or capture the moving object. Although a sensor node is capable of performing a variety of task, it has limitation as well. The main concern for the sensor nodes is its energy constraint nature due to battery-operated operation. So the main challenge for WSNs is achieving energy-efficiency utilizing proper battery lifetime as well as reducing computation cost.

A. The WSN Tracking and Localization Problem

Now a day, WSNs is considered as cluster-based organization of sensor nodes; where, sensor nodes are grouped and close together to form into static clusters and track object in a bounded region [3]. The general purpose for considering this type of architecture is to minimize energy consumption in large-scale WSNs. However, static clusters are bound to share information within cluster, so tracking inconsistency may happen at the boundary during object movement in boundary regions. To mitigate this problem, on-demand basis Dynamic Clustering [2] method is used during object enter and exit the boundary region of clusters. However, in such case energy cost gets higher for frequent cluster creation and deletion during dynamic clustering. Finally, inaccurate distance-based calculation in dynamic clustering has reduced the reliability and accuracy in object localization and tracking.

B. Objective of the Research

Based on the above observation, existing method [2] is suffering from the drawbacks of tracking robustness, energy-efficiency and localization inaccuracy. So, the principal objective of this research would be to take an initiative towards eliminating those problems by the Incremental Clustering-based tracking with Trilateration-based localization [4]. Fig. 1 illustrates the proposed technique for moving object tracking techniques in WSNs.

Stability-plasticity dilemma [5], is one of the most important issues associated with on-line learning, i.e., how can a system holds previous memories, learn new ones and dismiss

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the ineffective patterns. In general, the large scale WSNs should be adaptable with the changing location for upcoming learning and reserve them in the most stable way.

The proposed research is focused on incremental clusters formation at the boundary region of static clusters. Incremental clusters can share object's information within different static clusters elements. In parallel, Incremental Clustering Algorithm can retain some recent clusters for object tracking in already visited path.

In Fig. 1, a sample tracking route is denoted by dotted line, an object (here, a car) moves on that route. The picture visualizes the tracking sequence during object movement throughout the network.

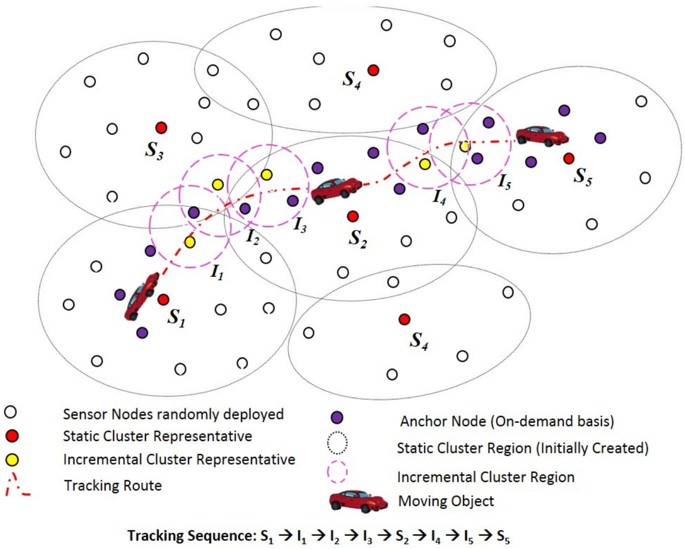


Fig. 1. Illustration of Proposed Technique for Moving Object Tracking.

Initially created static cluster S_1 can track the object until object is moving the boundary region of S_1. According to proposed research, Incremental clusters I_1, I_2, and I_3 are created on the boundary region of static clusters to continue the task of tracking. When an object passes from static cluster S_2 to S_5, two incremental clusters I_4 and I_5 are created to continue tracking in the boundary regions of S_2 and S_5. For precise localization of a moving object, the proposed work incorporates Trilateration-based calculation on previously identified anchor nodes, where receiver's RSSI (Received Signal Strength Indicator) based analysis is considered for anchor node selection.

C. Principal Contributions

The main contribution of this paper is to propose an incremental clustering algorithm for consistent object tracking at the boundary region of static clusters. The following principal contributions have been made towards achieving the objectives of the research:

- A complete and consistent algorithm for robust object tracking and accurate localization in WSNs.
- An energy efficient Incremental Clustering Algorithm for object tracking at the boundary region of static clusters.
- Performance of the proposed work in terms of consistency and network lifetime has been examined and analyzed through extensive simulations.

The rest of the paper is organized as follows. In Section II, literature review of this research been discussed. Section III elaborates the problem formulation and relative solution space of the proposed work. Section IV explains the proposed algorithms while Section V gives some details of the simulation environment with results. Finally, Section VI concludes the paper with discussion and future scope.

II. LITERATURE REVIEW

In Typical, tracking algorithms can be classified mainly based on the network architectures: Tree-based, Model-based, Cluster-based, Prediction-based and Hybrid-based algorithm. Networks in the Tree-based architecture are usually represented as a hierarchical tree. Examples of this type of architecture are STUN (Scalable Tracking Using Networked Sensors), DCTC (Dynamic Convoy Tree based Collaboration) and OCO (Optimized Communication and Organization) [6]. H. T. Kung [7] has proposed STUN as a network grid and estimate cost function from the Euclidean distance between two nodes. Based on the cost function network is constructed like a tree. Zhang and Cao [8] have proposed DCTC algorithm, for moving object tracking a tree is constructed dynamically. Depending on the object's precise location, a group of nodes is responsible for tree construction which further represented as a logic tree without reflecting the physical structure of the established network.

An information-driven dynamic sensor collaboration mechanism for object tracking has been proposed by Zhao [9]. Brooks [10], presented a distributed entity-tracking framework for sensor networks. Wang [11] has proposed a suitable location estimation technique for object tracking in WSNs. Vigilnet [12, 13], a real-time energy efficient object tracking system, is designed and implemented in the arena of WSN. In [14], a distributed Time division multiple access (TDMA) based scheduling algorithm for moving object tracking in ultrasonic sensor networks was designed. In [15], a secure location-aware algorithm is proposed which is able to defend the network against usual attacks.

However, to make balance between energy consumption and sensor collaboration, a lot of Dynamic Clustering protocols have been proposed for object tracking in WSNs. An adaptive dynamic cluster-based tracking (ADCT) protocol is proposed by Yang [16]. The purpose of this protocol is to select cluster heads on-demand basis. A simple prediction-based algorithm is used to wakes up nodes which further participate to form clusters during moving of the object throughout the network. A balance between missing rate and energy consumption is proposed by Jamali [17, 18], through his Dynamic Clustering mechanism. Working with camera network for object tracking, Medeiros [19], proposed an efficient Dynamic Clustering algorithm.

Prediction of object's motion and next location some existing and well-known examples of are DPR (Dual Prediction-based Reporting) and DPT (Distributed Predicted Tracking). The aim of these prediction-based architectures is to reduce energy consumption by keeping most of the sensor nodes in sleeping state. Current research trend focuses on organizing the sensor nodes into some static clusters [20-22]. Furthermore, tracking protocols have followed the cluster structure of the nodes in LEACH [3] and HEED [23]. DPR [24] is proposed by Yingqi Xu that can predict object's next location sitting on sink and sensor nodes.

In a recent research of hybrid clustering-based object tracking (HCTT) [2], on-demand basis dynamic cluster formation is considered during object enter and exit transitions in the boundary regions of static clusters. However, the protocol is an energy consuming protocol due to frequently cluster formation and dismisses in the boundary regions. HCTT [2] cannot retain any cluster even if it is the recently created one. The proposed Incremental Clustering algorithm is developed based on the method proposed in [25], where sensor node pattern is firstly learned from the environment, then cluster is formatted retaining for future use.

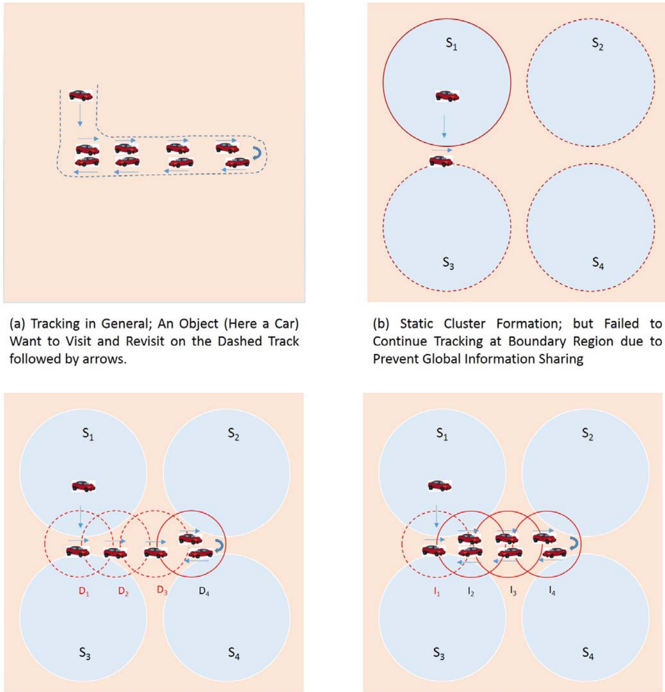
III. Problem Formulation

A. Boundary Problem

As of now, the task of tracking is continuing with the different clustering techniques. Based on the communication range, sensor nodes are partitioned into several static clusters to continue energy-efficient tracking task with a low-cost. An example is demonstrated in Fig. 2a, visualizing the general tracking sequence of an object, where object can revisit the tracking path.

In Fig. 2, clusters are represented as circular shape, solid lines indicate active clusters and dashed lines indicate dismissal of clusters. Considering Fig. 2b, four static clusters are formed to continue the tracking of an object. During tracking, when an object is present in any static cluster, sensor nodes of that cluster are responsible to track that object while other clusters are kept free from communication. In this way, energy-efficiency is ensured in this technique. But when the object moves to the boundary region, tracking can be lost due to static clustering where global information sharing is refrained. So, only S_1 cluster can track the object when object is inside of this cluster and whenever the object is at the boundary of S_1, tracking can be lost due to prediction error of next cluster.

In this regards, on-demand dynamic clusters can be formed at the boundary region of static cluster [2]. Sensor nodes from different static clusters can share information temporarily when the object is within that cluster. When an object exits from the static cluster another temporary cluster will be created and the process will continue dismissing the previously created one. In Fig. 2c, the tracking process in boundary region is showed for dynamic clustering. However, if the object wants to revisit the track, dynamic cluster will re-create the recently created clusters as those clusters are no longer exist. Although dynamic clustering is efficient for collaborating with local sensors, but ultimately it suffers too much overhead for cluster construction and dismissal. Since the object moves, D_4 cluster can continue tracking as object is still presented in that cluster, whereas D_3, D_2, and D_1 has to be created if when object wants to revisit the track, which will consume more energy.



(a) Tracking in General; An Object (Here a Car) Want to Visit and Revisit on the Dashed Track followed by arrows.

(b) Static Cluster Formation; but Failed to Continue Tracking at Boundary Region due to Prevent Global Information Sharing

(c) Dynamic Cluster Formation at Boundary Region; but Energy Consumption is High When Object is on the Revisited Track

(d) Incremental Cluster Formation at Boundary Region; Energy Efficient due to Retain Recently Formed Clusters

Fig. 2. Boundary Problem Visualization. (a) Considering a Tracking Sequence, (b) Static Clustering Limitations for Tracking, (c) Dynamic Clustering Energy Consumption at Boundary Region and (d) Incremental Clustering Energy Efficiency as our Proposed Solution.

B. Solution Space

The proposed research presents an Incremental clustering at the boundary of static cluster. In Fig. 2d, Incremental clustering algorithm can create clusters incrementally at the boundary region whenever it learns a new input sequence from the environment. This technique can not only create clusters, but also can retain recently created clusters which in turn increase energy-efficiency. During learning, if the cluster representative is experienced with new pattern of sensor nodes it will create a new cluster, otherwise updates the existing clusters. I_4, I_3 and I_2 clusters can continue tracking when the object wants to revisit the track. Due to memory saving and energy-efficiency I_1 cluster is created only once then dismiss. Therefore, only I_1 cluster has to be created twice if object wants to revisit the visited track. Comparing with above mentioned clustering techniques, incremental clustering seems to be most energy efficient, since it requires less communication for cluster formation.

IV. Incremental Clustering based Tracking

The proposed work provides a suite of algorithms for handling object tracking problem at the boundary region as well as provide localization in WSNs. Although Dynamic Clustering can continue tracking in boundary region, but it is energy consuming costly technique due to creating and re-creating cluster rather than retaining already created clusters for object re-tracking in already visited path. In this regard, a naive algorithm, Incremental Clustering is proposed for energy efficient and low-cost solution.

A. Object Tracking and Localization Algorithm

The proposed idea deals with the problem of boundary localization, energy consumption and object localization as optimal as possible in some sense. The complete algorithm for object tracking and localization in Wireless Sensor Network is described in Algorithm 1. The proposed algorithm focuses on three basic parts: sensor network initialization, object tracking techniques and finally, moving object localization for WSN.

Algorithm 1: Object Tracking and Localization in WSNs.

Requires: Initialized Network, Static Clusters and Cluster Heads, Observation Trajectory.

Ensures: Tracking and Localization.

Initialize Network with Static Cluster
Boundary Node Formation
while** (object detect) **do
    if** tracking is in safety region **then
        Tracking Continue with Static Cluster Representative
    ***else** (object is in boundary region)*
        if** Observation Trajectory Satisfies Membership Condition of Incremental Clusters **then
            Update Clusters (Incrementally created) with new Observation Trajectory
        else
            Create a new Cluster using Incremental Clustering Algorithm
        Tracking Continue with Increment Cluster Representative
        end if
    RSSI Analysis to Calculate Anchor Node from Selected Cluster
    Localization using Trilateration Algorithm
end while

B. Incremental Clustering Algorithm

The defining task of tracking in the proposed work is cluster-based object tracking which in turn refers to the object's different movements in the network. Algorithm 1 directs successful line of work in object tracking in two ways. Firstly, when object presents inside of any static cluster, the representative of that cluster will monitor the object based on node sensing of that cluster. Secondly, when object is in the boundary region of static cluster, on-demand basis cluster will be created using Incremental Clustering for smooth tracking of object in the boundary region.

This paper proposes the details of incremental clustering algorithm incorporating with Gaussian Adaptive Resonance Theory (GART) [25]. The important properties of GART are as follows:

1. Combining new information without tarnishing previously learned data, cluster can grows incrementally. Network can retain previously learned information which can solve stability-plasticity dilemma. In this way, object tracking can continue smoothly in the border region with energy-efficiency.
2. Clusters in a network follow Gaussian distribution [26] with mean and covariance. As sensors are deployed in 2D space Gaussian distribution can be used.

Similar nodes will be close together in the point distribution space, away from other nodes representing dissimilar patterns. These groups or clusters can be represented the current tracking pattern. The mean of the pattern in each cluster is used as representative. Each Cluster is defined by mean vector μ_i, covariance matrix $\sum_i$, and a weight value w_i. The parameter, n_i represents the number of cluster component (count) presents at any time in the network. During tracking the network is initialized with two parameters: baseline vigilance parameter ρ and initial covariance matrix $\sum_0$. Choice of appropriate values for the above mentioned parameters significantly improves network performance.

During tracking the activation value for each cluster is calculated by the conditional density of an observation trajectory O_t as in (1):

$$p(O_t|i) = \frac{1}{(2\pi)^{M/2}|\Sigma_i|^{1/2}} \exp\left[-\frac{1}{2}(O_t - \mu_i)^T \Sigma_i^{-1}(O_t - \mu_i)\right] \quad (1)$$

where *M* is the dimensionality of the input patterns.

After calculating activation value using (1), the highest probability of a cluster matching with observation trajectory is calculated using (2).

$$K = \arg\max_i p(O_t|i) \quad (2)$$

However, the selected cluster will update only if it passes the vigilance criterion in (3).

$$\exp\left[-\frac{1}{2}(O_t - \mu_i)^T \Sigma_i^{-1}(O_t - \mu_i)\right] \geq \rho \quad (3)$$

If the current winner cluster is failed to pass the vigilance criterion, the cluster is not allowed to update its weights. If there is no available cluster found, a new cluster will be created with only one element i.e., observation trajectory O_t. However, if the winner cluster passed the vigilance criterion, the cluster is selected to update the count, mean, covariance and weight according to (4) – (7). Other cluster will lose their weights according to (7), to keep a certain number of clusters in the network.

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

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

$$\Sigma_K = \left(1 - \frac{1}{n_K}\right)\Sigma_K + \left(\frac{1}{n_K}\right)(O_t - \mu_K)(O_t - \mu_K)^T \quad (6)$$

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

A new cluster will be formed only if the observation trajectory (current pattern) does not belong to any cluster. O_t, is the only member of new cluster, with weight $w_K^{(t+1)} = 0$ and count $n_K = 0$, and the cluster with lowest weight is removed if *L* is reached. To reduce communication cost and limit memory requirements, up to *L* clusters are kept. In this way, cluster grows incrementally by learning from environment and can retain those clusters for energy-efficiency.

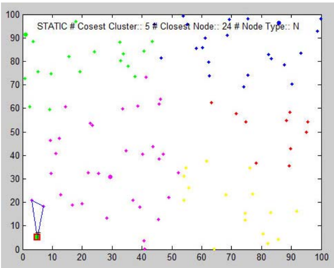
V. Simulation and Performance Evaluation

A. Experimental Setup

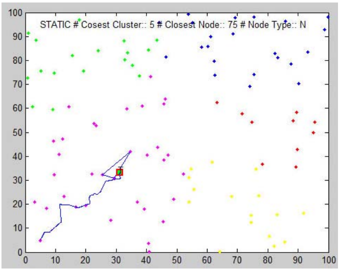
Using Matlab Simulator, 100 nodes are deployed randomly into the area of 100 x 100 m^2 for moving object monitoring. Considering an application of radio transmission of energy dissipation during transmit and receive, assuming a simple model where the radio dissipation rate is 50 nJ/bit to operate the transmitter or receiver circuitry and amplifying rate is 100 pJ/bit/m2 for the transmit amplifier to achieve an acceptable ratio [2]. For channel transmission, we have assumed r^2 energy will be lost [27]. In this way, to transmit a *k*-bit message the number of node will significantly dead after a long run.

B. Experimental Results

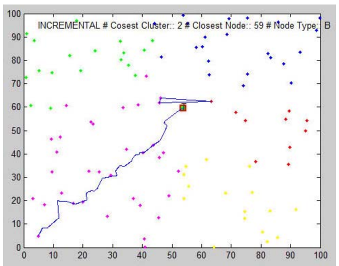
Fig. 3 visualizes a sample simulation result of consistent tracking sequences considering both Static Clustering (LEACH protocol) and Incremental Clustering based object tracking. The results indicate incremental clusters are formed when object is in the boundary region of static clusters to continue the task of tracking.



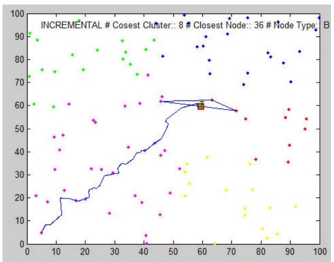
(a) Deployment of Sensor Network and Static Clustering based Object Detection.



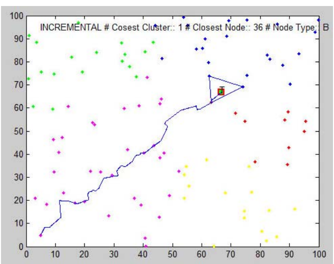
(b) Object Tracking Inside static Cluster using LEACH protocol.



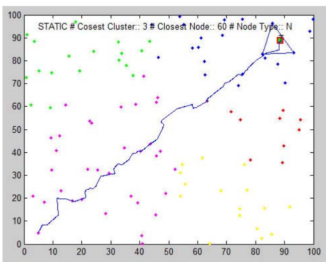
(c) Incremental Clustering based Object Tracking at the Boundary Region of Static Clusters.



(d) Consistent Object Tracking at the Boundary Region with Incremental Clustering.



(e) Consistent Object Tracking at the Boundary Region with Incremental Clustering.



(f) Object Tracking Inside static Cluster using LEACH protocol.

Fig. 3. Consistent Object Tracking using Proposed Incremental Clustering at the Boundary of Static Clusters.

We also observed the network lifetime as shown in Fig. 4, for both Incremental Clustering and Dynamic Clustering [2] by conducting 20 experiments. With 100 nodes in the network, we tracked the object movement in diagonal (as shown in Fig. 3).

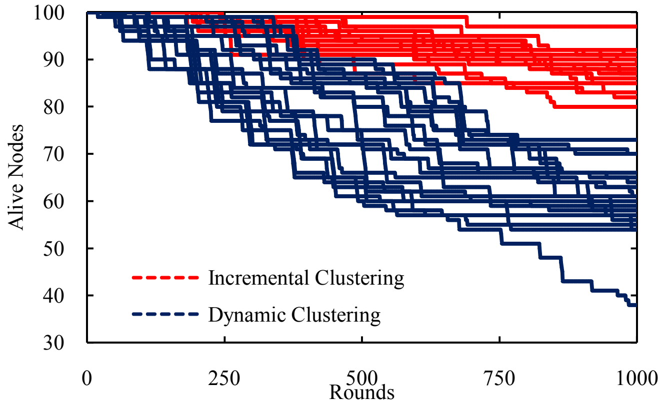


Fig. 4. Network Lifetime Observation for 20 experiments: Incremental Clustering vs. Dynamic Clustering.

The average network life time is shown in Fig. 5, which clearly depicts that network is more stable and energy-efficient for Incremental Clustering based tracking. During tracking, an average of 40 nodes goes down for choosing Dynamic Clustering, whereas only 12 nodes dies for choosing Incremental Clustering at the boundary region of static clusters. As we know, Dynamic Clustering create clusters on-demand basis and dismiss whenever object left that place, it consumes more energy due to frequent cluster head selection, member formation, and overhearing. In this regard, Incremental Clustering outperforms the Dynamic Clustering technique.

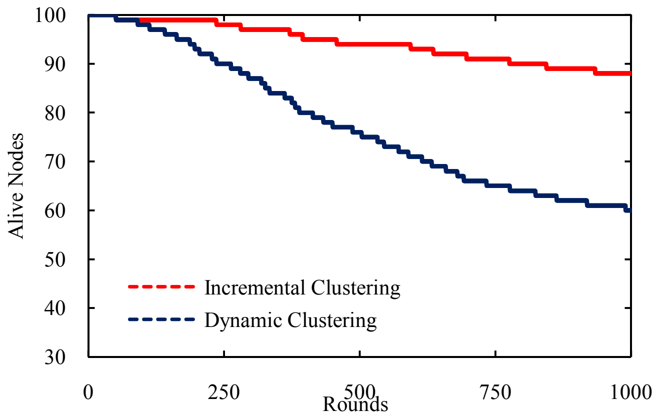


Fig. 5. Average Network Lifetime Observation: Incremental Clustering vs. Dynamic Clustering.

VI. Conclusions

In this paper we have developed an approach for real-time incremental learning of continuous flow of object's tracking patterns. The clusters are updated automatically and incrementally using Gaussian ART, which aggregates the new information as observed and organizes the acquired information in an efficient growing and self-organizing manner. In response to new information, the incremental learning algorithm adapts to add this information without corrupting previously learned knowledge. As static clusters are prohibited to share global information, incremental clusters are created at the boundary of static clusters to keep smooth tracking throughout the network. Finally, the proposes Incremental Clustering outperforms the state of the art Dynamic Clustering technique in terms of energy-efficiency, cost and network lifetime.

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