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# Efficient Tracking Using Hybrid Clustering and Low Power Prediction Mechanism

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**ABSTRACT**

**Background:** Target tracking is an important application of wireless sensor networks (WSNs). Since the sensor node have non rechargeable battery source, the network life time and the accurate prediction of the targets are the important parameter while deploying target tracking network. Cluster based techniques are widely used to improve network life time and scalability. **Objective:** A fast energy efficient high accuracy target tracking scheme is proposed here, which is based on location prediction and hybrid clustering. In Hybrid clustering on-demand dynamic clusters are formed at boundary regions and the tracking task can be handed over smoothly from one cluster to another. In location prediction, when the target moves, the location of the target is predicted and the sensors of the respective clusters is waked up. Static clusters and on-demand dynamic clusters alternately manage the target tracking task. **Results:** Simulation results show that our proposed prediction algorithm has consumed less energy and low complexity as compared to existing predictors like linear predictor and Extended Kalman Predictors**.** **Conclusion:** It is proven that the proposed target tracking algorithm outperforms the existing algorithm in terms of increasing network lifetime, target tracking accuracy and it has very low missing rate

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## INTRODUCTION

Target tracking is known to be one of the core applications in battlefield monitoring, disaster management and patient monitoring. In recent years, research on target tracking in wireless sensor networks (WSN) becomes more and more popular. Target tracking in WSN applications should consider two main issues. First, the deployment of the WSN must be appropriate that is, the coverage and the connectivity problem are of two fold concern. Second, target tracking has its own characteristics, such as trajectory estimation, data association, data compression etc, should be addressed. Even though target tracking under WSN environment shares some similarities with traditional methods, we must consider its specialty since sensor nodes have limited power and computational capability which may not be ample for the complex signal processing algorithm in traditional target tracking (Shengnan Li, 2014).

A target tracking in WSNs can have several advantages (i) qualitative and fidelity observations (ii) signal processing accurately and timely (iii) increased system robustness and tracking accuracy. The sensed data is composed, processed and then routed to the desired end user through a designated base station (Mhatre, V. and C. Rosenberg, 2004).To improve the quality of tracking, sensors need to make accurate estimates of the location of targets. The important characteristics of the WSN are that power consumption constrains for nodes using batteries or energy harvesting, ability to cope with node failures, mobility of nodes, heterogeneity of nodes, scalability to large scale of deployment and ability to withstand harsh environmental conditions.

Target tracking schemes are divided into three typical categories: tree-based tracking, cluster-based tracking and prediction-based tracking. It is known that the cluster structure can provide benefits for large-scale WSNs. For example, it facilitates spatial reuse of resources to increase the system capacity (Lin, C.R. and M. Gerla, 1997). Normally, nodes surrounding the target collaborate with each other to estimate the location of the target. In (Chen, W.P., 2004; Yang, W.C., 2007; Walchli, M., 2007; Xing, X., 2000; Jin, G.Y., 2006; Medeiros, H., 2008), dynamic clustering approach, it dynamically wakes up a group of nodes to construct a cluster for local collaboration when the target moves into a region. Dynamic clustering is obviously an efficient way for local sensor collaborations because clusters formed

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at each time instant change dynamically, as the target moves. However, the dynamic clustering incurs much overhead for forming and dismissing clusters. Besides, dynamic clustering does not consider how to efficiently send data to the sink, which is another important aspect of target tracking. In contrast, the target tracking in (Yang, H. and B. Sikdar, 2003; Wang, Z.B., 2008; Wang, Z.B., 2001) uses the static cluster for the network scalability and energy efficiency. Static cluster does not mean that the cluster will not change during the network's entire lifetime, it for some rounds of data transmission. In (Chang, W.R., 2008; Zhibo Wang, 2013), a Hybrid clustering approach is used. The network is first divided into multiple static clusters, as the target moves the dynamic clusters are constructed and dismissed. In (Hsua, J.M., 2012; Xu, Y., 2004; Goel, S. and T. Imielinski, 2001; Bhuiyan, M.Z.A., 2010; Kim, H., 2006; Di, M., 2008) the prediction based schemes are used to predict the location of the target. In prediction based methods, the next location of moving object is predicted. During each defined time step, only some nodes near the predicted location are activated and other nodes stay in sleep mode as energy save state. But in prediction based methods the data transmission to sink may be costly, as the data may be redundant and more the communication distance.

In this paper we combine the Hybrid clustering method with the Low Power Prediction mechanism into predict the exact location of object and to improve the network lifetime and scalability by using clustering. After deployment we divide the network into static clusters, as the target moves the next location is predicted and the nodes are wake up according to the predicted location. When the target reaches the boundary area of a multiple cluster, the on-demand dynamic clusters are constructed, in order to avoid the prediction error.

Rest of the paper is organized in following structure; Section 2 briefs the characteristics of energy efficient target tracking. Section 3 presents the earlier works in target tracking based on clustering and prediction. Section 4 explored the detailed description of our proposed algorithm. In section 5 we analyze the performance our proposed algorithms with existing approaches. In section 6 we conclude our paper based on our simulation result.

## *2. Characteristics of Energy Efficient Target Tracking:*

In an energy-efficient WSN based target tracking scheme, all nodes should be initially in a sleep state, except nodes that are on the borders of the surveillance area. These border nodes first identify the target, and then they activate other nodes via external activation messages transmitted over a low-power channel. A tracking process is generally divided into successive tracking steps whose durations are constant or variable depending on the estimation/prediction algorithm. In each tracking step, the activation message is disseminated in a zone called activation zone whose range depends on the estimated target velocity and the measurements' error in the current tracking step.

After network initialization, the estimation/prediction algorithm computes a reliable estimation of the target state. The filtering algorithm generates estimation for the current tracking step and one or more predictions for the next tracking steps. If the target has a dynamic behavior during the current tracking step, then a cluster and/or a tree reorganization is triggered to follow-up the target trajectory. It is the current leader or the current root that generates target estimation and reports data to the sink.

A typical target tracking scheme should consider the following elements to be energy efficient:

1) Quality of detection: Depending on the percentage of network coverage (which is related to the network initial deployment, nodes' sensing ranges, network density, etc.), target can be watched by one or more nodes that generate correlated readings about its state. A target tracking scheme should be able to measure the information utility of these data to decide about, which nodes to select for the next tracking step? How long should be the activation range? How many nodes should be selected? Etc. This measure helps in computing the current estimation error.

2) Estimation/prediction algorithm: The prediction algorithm should be distributed and light-weight depending on the equation state model of the target (linear or nonlinear), the noise model of the sensors readings (Gaussian or non-Gaussian), the target sensing modalities (single modality or multiple modalities) and the given limited resources of sensor nodes. The Kalman Filter algorithm (KF) (Welch, G. and G. Bishop, 1992) is an accepted solution for estimation/prediction since it is easy to implement. The algorithm is based on a two-step recursive procedure, namely: update step and prediction step and it converges for linear systems. However, for more complex equation state models, the other data filtering algorithm such as: Particle Filter (PF) (Kennedy, J. and R. Eberhart, 1995), Variational Filter (VF) (Teng, J., 2010), Extended Kalman Filter (EKF) (Candy, J., 2006), Unscented Kalman Filter (UKF) (Wan, E. and R. Van Der Merwe, 2002), etc are used.

3) Data reporting mechanism: After the target state estimation and prediction, choosing the data reporter node is another issue. Typically, when connectivity is provided, nodes that are close to the target with maximum energy resources should be selected. However, network reconfiguration may lead to a situation where the reporter node is far away from the sink and/or the target. Solutions such as the selection of backup reporter nodes or the

establishment of a hybrid (static/dynamic) network structure can be applied.

4) Activation mechanism: The activation range depends on the target velocity. To avoid target loss, a multi-step activation mechanism with dynamic activation range can be applied. The activation plan can be static (pre-established at the beginning) or dynamic depending on the current estimated measurements' error.

5) Logical network structure: To optimize communications, a flat network structure is not the better solution. Clusters or trees can be temporarily constructed to localize the data fusion process. However, the target tracking scheme should tackle some problems related to the dynamic nature of WSN such as: leader election, cluster/tree reconfiguration, clusters boundary determination, etc

### *3. Related Work:*

In the last few years, a lot of protocols and algorithms were developed for collaborative target tracking in WSN. Here we present a few methods based on clustering and prediction schemes. To balance the energy consumption and sensor collaboration, a lot of dynamic protocols have been proposed for target tracking. A decentralized dynamic clustering protocol for acoustic target tracking was proposed in (Chen, W.P., 2004), which relies on a static backbone of sparsely deployed high capacity sensors. In (Yang, W.C., 2007), the authors proposed an adaptive dynamic cluster-based tracking (ADCT) protocol that dynamically selects cluster heads and wakes up nodes to construct clusters with the help of a prediction algorithm. A dynamic convoy tree-based collaboration (DCTC) framework to detect and track the mobile target was proposed in (Walchli, M., 2007). The dynamic clusters are constructed by adding and pruning some nodes in the convoy tree as the target moves. Another protocol called Herd-Based Target Tracking Protocol (HTTP) is proposed in (Xing, X., 2000). It is based on a three state-transition model, namely: sensing, sleeping and tracking.

Each node computes its weight and decides to participate in the tracking process or not. Nodes that are in the tracking state (Herd Nodes) form a cluster surrounding the target. The backup herd node is a node that has the same role as the herd node, but it does not send data to the base station. The authors of (Jin, G.Y., 2006) proposed a dynamic clustering mechanism for target tracking in WSNs that balances the missing rate and energy consumption. A dynamic clustering algorithm for target tracking in wireless camera Networks was proposed in (Medeiros, H., 2008). Several target tracking protocols is based on static cluster structure. Sensor nodes are organized into clusters by using suitable clustering protocols, such as LEACH (Heinzelman, W.B., 2002) and HEED (Younis, O. and S. Fahmy, 2004).

With the cluster structure, the authors of (Yang, H. and B. Sikdar, 2003) proposed a distributed predictive tracking (DPT) protocol that predicts the next location of the target and informs the cluster head about the approaching target. The corresponding cluster head then wakes up the closest three sensor nodes around the predicted location before the arrival of the target. In (Wang, Z.B., 2008), the authors proposed a hierarchical prediction strategy (HPS) that also relies on cluster structure for target tracking and implemented a real target tracking system in (Wang, Z.B., 2001). The Hybrid Clustering algorithms were presented in (Chang, W.R., 2008; Zhibo Wang, 2013), which combines the features of static clustering and dynamic clustering in order to avoid the boundary problem of dynamic clustering. CODA uses a hybrid clustering approach by constructing a static-cluster backbone and the boundary sensors of these clusters form a dynamic cluster to monitor the continuous object profile. CODA also uses the Graham Scan algorithm to determine the sensors located at the boundary of the cluster by the cluster-head. Boundary detection is based on the number of static clusters that detect the object. The cluster-head is notified via sense messages. Then, it executes the Graham Scan algorithm and organizes its boundary sensors within a dynamic cluster. When the object boundary moves out of the sensing range of the current boundary sensors, new clusters are formed. In order to solve the boundary problem, another Hybrid algorithm called Hybrid Cluster-based Target Tracking (HCTT) was proposed in (Zhibo Wang, 2013). According to this, the boundary problem increases the tracking uncertainties and to solve it, HCTT checks whether there exist neighboring nodes that belong to another cluster or not. If yes, then these are boundary nodes and the cluster region is divided into three types: safety region, boundary region and alert region. Consequently, the dynamic cluster includes active boundary nodes that detect the target. The hand-off between static and dynamic clusters is based on the sensing data received from the nodes within these different regions.

In prediction based methods, the next location of moving object is predicted. Then, during each defined time step, only some nodes near the predicted location are activated and other nodes stay in sleep mode as energy save state. For example in (Xu, Y., 2004), advantages of prediction mechanism in a cellular network, leads to a limited search space of object tracking and so strongly reduces the paging overheads. In (Hsua, J.M., 2012) authors use prediction mechanism to decrease the number of active nodes. So in each time step, just one hop surrounding nodes of the next predicted location of the object would be activated. In (Goel, S. and T. Imielinski, 2001), by using the past sensing history and spatial and temporal knowledge of sensors, the future location can be predicted, and just a few number of nodes are activated. In (Xu, Y., 2004) the regression based prediction and Kalman filter are used.

The linear predictor is used to predict the next position of object in which the current location and the previous location of object are taken into account. Authors in (Kim, H., 2006) assume that the object sometimes move non-linear, so they use moving average estimator with a proposed correction mechanism. In (Di, M., 2008), Kalman filter based methods such as Extended-Kalman Filter and Sign of Innovation-Kalman Filter were studied. So far there is no research works about prediction based WSN tracking object with variable velocity. So the previous methods lost the object with variable speed during tracking process. It is clear that the missing rate of the object leads to high total energy consumption in the network. In WSN object tracking mechanisms, the energy consumption is dependent on the missing rate, since the nodes must find the lost object via recovery mechanism as a high energy consumption procedure. In an accurate predictor, fewer nodes would be activated for collaborative tracking and leads to negligible consumed energy and transmission overheads. To address this concern, we defined a different kind of mobility model for moving object and a new prediction based energy efficient and high accurate tracking method in a clustered sensor network. According to our proposed method in each time instance, only some nodes with the following characteristics will be selected for tracking and other nodes go to the power saving mode: 1) near to the target, 2) have more energy, 3) less distance to their head node.

## *4. Proposed System:*

### *4.1. System Model:*

We assume that a large-scale WSN consisting of n static sensor nodes is deployed in a two-dimensional area of interest for detecting a single moving target. The sink node is deployed at the center of the network. We assume that sensor nodes are randomly deployed and each sensor node has an identical communication range rc. The sensor nodes within the communication range of a sensor node are called its neighbor nodes. In general, the received signal of a sensor node about the target reduces with the increase of the distance between the sensor node and the target. We organize the WSN to m clusters by using the clustering algorithm presented in (Malathi, L. and R.K. Gnanamurthy, 2012). Each cluster has one cluster head which is responsible for reporting the location of target to sink. We also assume that each node aware of its own location and some local information of its neighbors but has no global topology information.

To ease the description of the proposed algorithm, we adopt the following notations throughout the paper:

(i) n: the number of sensor nodes
(ii) m: the number of static clusters
(iii) rc: the communication range of each node
(iv) rs: the sensing range of each node
(v) (Six, Siy) : the position of the sensor i
(vi) (Xt,Yt): the position of the target
(vii) (⍰): the location of the target at time ⍰.

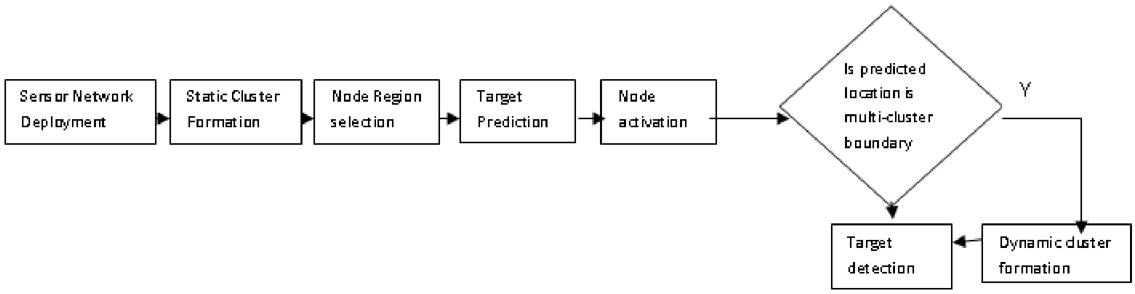


**Fig. 1:** Overview of Proposed Algorithm.

### *4.2 Node Region Selection:*

In our proposed algorithm, a dynamic cluster will be constructed when the target approaches the boundaries of multiple clusters. A challenging issue is how the system finds that the target is approaching the boundaries of multiple clusters? Here, we use the alert nodes to solve this issue in a fully distributed way. The nodes in the static clusters are divided into three different classes based on its location. The three classes are Boundary class, internal class and alert class. Each node in the network has a set of neighbors. If all neighbors of the node belong to the same cluster Ci, the node is in internal class, If some neighbors of node are belong to the same cluster Ci and some neighbors belongs to another cluster Cj then the node is in gateway class. If some neighbors of node belong to the same cluster Ci and other neighbors belongs to other cluster Cj, Ck then the node is in alert class. The fig. 2 describes the three classes of nodes. If the target reaches the alert node, the dynamic clustering procedure is started.

### *4.3. Target Prediction:*

It is assumed that each sensor node can find the approximate angle of the target in its sensing range. So the nonlinear measurement model for sensor i in{1, 2, ..., n} at time instant t is as follow:

$$\theta i = \tan\left(\frac{Yt - Siy}{Xt - Six}\right) + ei$$

where (Six, Siy) is the position of the sensor i, (xt, yt) is the real position of target at time t and vi is sensing error, which is zero mean and Gaussian distribution with constant standard deviation of σθ.

Based on assumption that the node sensing errors are sufficiently small, head node can adopt Least Square algorithm to determine target location, with node sensing collaboratively. The true value of angle can be written as

$$\tan(\theta i) = \frac{\sin(\theta i)}{\cos(\theta i)} = \frac{Yt - Siy}{Xt - Six}$$

In presence of noise, we can write the location of the X as

X=H/F

FX=H

Where X is the location of the target F and H matrices are given by

$$F = \begin{matrix} sin\theta 1 & cos\theta 1 \\ \vdots & \vdots \\ sin\theta n & cos\theta n \end{matrix}$$

$$H = \begin{bmatrix} S1x.Sin\theta 1 & - & S1y.Cos\theta 1 \\ & \vdots & \\ Snx.Sin\theta n & - & Sny.Cos\theta n \end{bmatrix}$$

The least square solution of FX is

$$X' = (\mathrm{F}^{\mathrm{T}}\mathrm{F})^{-1} H F^{\mathrm{T}}$$

Where X' is the estimation of target position.

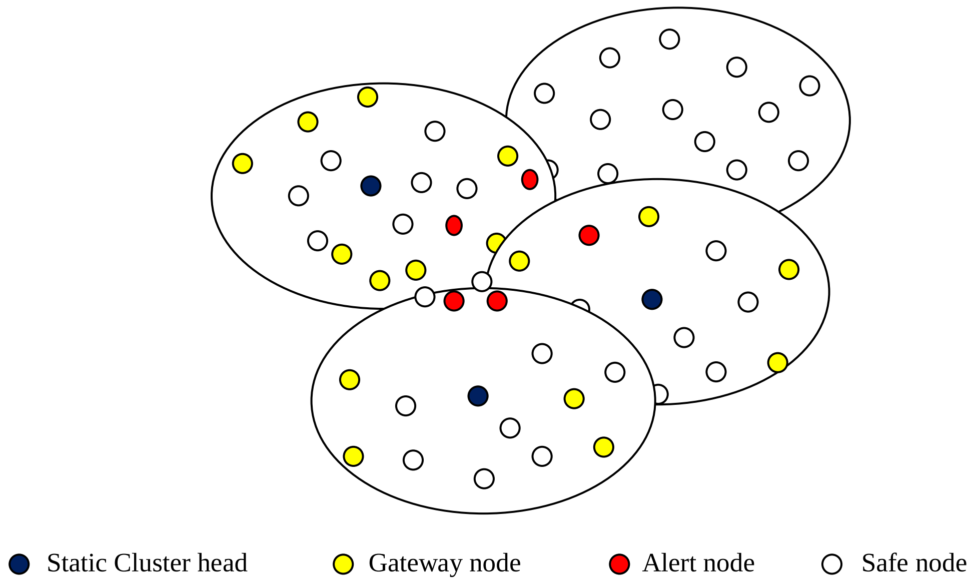


**Fig. 2:** Illustration of different types nodes under target tracking environment.

Here we assume that mobile target moves for a random period of time in random direction with speed and acceleration that are in ranges [0, amax] and [0, vmax] respectively. In fact we use Random way point and Constant Acceleration Model (RCAM) for target mobility in which Random way point model uses pause times before changing three parameters: speed, direction and acceleration. Proposed predictor is based on prediction error which is described by the angle between the actual location and previously predicted location, denoted by Ωt. It is assumed that moving object has constant acceleration. So after predicting the speed of object in the next time step, we try to find next position of the object based on prediction error. If Ωt is in the range [−α, α], the next velocity of moving object at time t + 1 is predicted by:

$$v(t + 1) = 2 \times v(t) - v(t - 1)$$

Then the next location of object is predicted as follows:

$$x(t + 1) = v(t + 1) \times T \times \cos\varphi + x(t)$$

$$y(t + 1) = v(t + 1) \times T \times \sin\varphi + y(t)$$

***4.4. Target Tracking Mechanism:***

All nodes except outer boundary nodes of surveillance area are in sleep mode and just can listen to low power communication channel to check alarm messages which consumes less energy. When the target enters into the surveillance area, the boundary node which detects the target sends the wakeup message to its cluster head along with position of the target. The node also predicts the next location of the target using our low power prediction algorithm and wakeup its neighbors accordingly. Each node which find the object, stay active and others go back to sleep mode. In active mode all components of the node are active. The Head node collects the target position from its members and send the information to the sink periodically. As the target moves, the nodes in the static cluster detects the location, predict the next location of the target and wakeup its neighbors accordingly. If the target reaches the boundary of the static cluster, that is the gateway class nodes, the current static cluster head send the wakeup message to the next static cluster head with the predicted location of the target. The smooth, static to static handover of target is done. The head node wakeup its members and target tracking continues. If the target reaches the alarm class then, the dynamic clustering is constructed.

#### *4.5 Dynamic Cluster formation:*

If any alarm class node receives the wakeup message from its neighbors, it sends the Dcluster_alert message to its neighbors of alert class. Once the target is detected by the alert class node, it sends the Dcluster_init message to its neighbors, the nodes respond with Dcluster_member message. The dynamic cluster was formed and the initiation node becomes cluster head of dynamic clusters. The DCH receives the node information from its members and if the next predicted node is the internal node or gateway node the current node send the wakeup message to its CH. The DCH updates the node information to its CH periodically. If the internal node or gateway node sense the target, it send the information both to DCH and CH and it send the Handover_req message to DCH with the CH information. The DCH forward the Handover_Req message to its CH along with the next CH information. It also perform the dynamic to static handover to its CH and the previous CH smoothly handover the details about the target to the new CH.

#### *4.6 Data Transmission:*

The Static cluster head is responsible for updating the target details to sink periodically. After static cluster construction the data transmission tree is constructed by having sink as root, CHs as first level children and so on. The CH forward the target details through this tree along the path.

## RESULTS AND DISCUSSION

In this section, we analyze the performance of proposed target tracking scheme through simulation using MATLAB. First the performance of our proposed filter is analyzed and compared with the Existing filters such as Linear and the modified version of Kalman filter (EFK). The prediction error and the missing rate are the parameters we considered for evaluating the predictors. The second part of this section evaluates the overall algorithm, as the boundary problem is discussed in the paper, we analyze the performance using the parameters energy utilization, network lifetime, node utilization, overhead and target miss probability.

Simulation Parameters:

| | |
|---|---|
| Number of Sensor Nodes | 500 |
| Node Distribution | Random |
| Network Dimension | (1000,1000) |
| Location of the Sink | (500,500) |
| Nodes initial energy (K) | 5 J |
| Transmitter circuitry dissipation $\varepsilon mp$ | 10 pJ/bit/m2 |
| Amplifier dissipation multipath $\varepsilon fs$ | 0.0015 pJ/bit/m4 |
| Eelec | 50nJ/bit |
| Message size | 1000bits |
| Control message size | 50bits |
| Sensing radius | 20m |
| Transmission range | 100m |
| Target Movemnet | random-way point model |

We also considered the target have the maximum acceleration amax = 15m/s2, the maximum velocity vmax = 30m/s and variance matrix of process noise Q = 52 × I2×2. For the predictor the bound of the prediction location error is α = 15 degree. We use a simplified energy consumption model which takes statistics of the energy dissipation whenever a node transmits or receives messages. The energy spent for transmitting an l-bit message over distance d is

$$ETx(l,d)=\begin{cases} l\times Eelec + l\times \varepsilon fs\times d^2, d\le dl \\ l\times Eelec + l\times \varepsilon mp\times d^4, d > dl \end{cases}$$

Where $\varepsilon fs$ is the energy consumed by free space model, $\varepsilon mp$ is energy consumed by multi path amplifier circuit and dl is fixed as 75m.

To receive this message, the expended energy is ERx(l)=l×Eelec

Accuracy of Predictor:

First we compare the accuracy of four mentioned predictors which is determined by square root of the difference between predicted and actual location of the object in two dimensions. The prediction error is given by

$$Error^t = \sqrt{\left(x_p^t - x_r^t\right) + \left(y_p^t - y_r^t\right)}$$

where the $Error^t$ is the prediction error of predictor at time t. The following fig.3 shows the accuracy of various filters.

The linear filter has the highest prediction error and our proposed algorithm has very low prediction error. The missing rate of proposed predictor is very low in comparison with other predictors especially in random way point mobility model, where after pause time the three main parameters: direction, velocity and acceleration would be changed. The accuracy of predictor has direct effect on missing rate so the consumed energy is strongly reduced. Since the sensor have non chargeable energy source, it is important to improve the lifetime of WSN. The life time of the proposed filter was highly influenced by number of dynamic cluster formed, number of nodes in active state and many more factors. We used the following parameters to evaluate our proposed algorithm.

Effectiveness: Number of dynamic cluster formed over simulation time for the random movement of a target around the surveillance area. Less number of dynamic cluster leads to less overhead.

Coverage: Percentage of nodes active over the simulation time. Number of active sensors directly influences the network lifetime.

Missing probability: Probability of sensor nodes misses the target while tracking.

Energy consumption: The total energy consumed over simulation time.

We ignore the localization approaches, which may affect the performance of the target tracking.

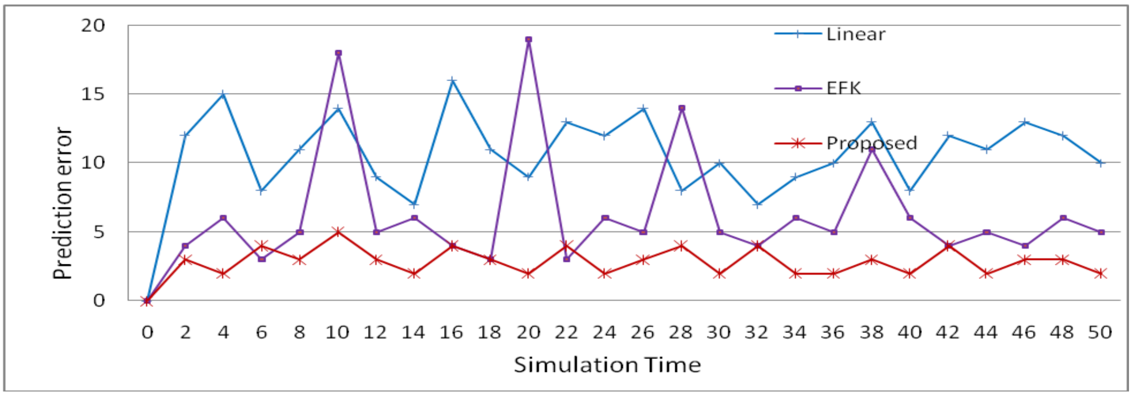


**Fig. 3:** Prediction Error.

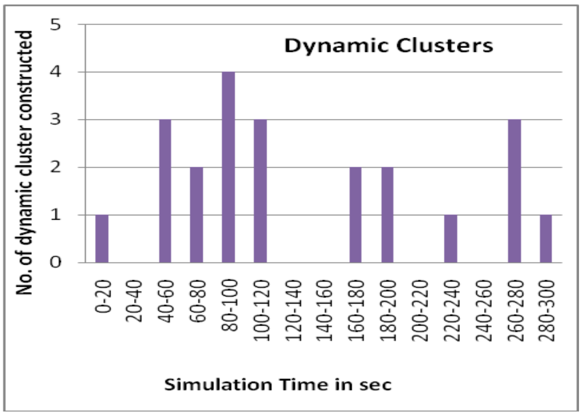


**Fig. 4:** Number of Dynamic Clusters Formed.

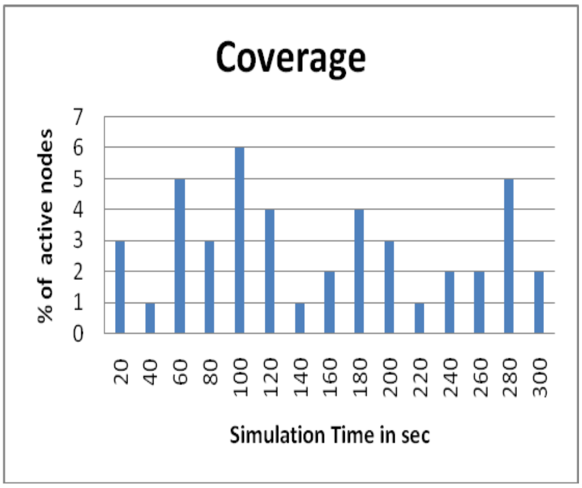


**Fig. 5:** Percentage of node active over time.

Fig 4 shows the number of dynamic cluster formed for a random movement of target for 300s. The proposed algorithm construct the dynamic cluster only when the target nearing multiple cluster boundary. According to prediction, there is no need to construct dynamic cluster at most times which reduces the handoff overhead that arrives in other protocols like HCTT. Fig 5 shows the percentage of nodes active for detecting the target in the surveillance area. In existing algorithms, the entire nodes in the cluster are active to estimate the location of target. We use low power prediction scheme which efficiently predict the target location and only nodes near by the target is active. Other members of stable cluster are in sleep state, which increase overall lifetime of Network. Except outer boundary nodes which are always in wakeup state, ie, maximum of only 6% nodes are in active state.

Fig 6 shows the effect of prediction error on target missing probability. Missing probability of DPT is higher than others. DPTC achieves zero missing probability when the production error is less than 0.5. The other algorithm including our proposed algorithm achieves 0 for all time. The proposed algorithm uses the low power predictive scheme, so it achieves 0. The HCTT does not rely on prediction algorithm, so prediction error has no effect on HCTT. But all nodes wake up during target tracking which waste the energy of the sensor node ADCT and in our proposed algorithm, the missing probability is not affected by the production error ie, rc ≥ 2 rs. To evaluate the energy efficiency of our proposed algorithm, we compare the consumed energy over specified time duration for predefined random movement of target in the surveillance area. The Fig.7 Shows the consumed energy of the protocols like DPT, DCTC, ADCT, HCTT and our proposed solution. The proposed algorithm outperforms other algorithms in terms of energy efficiency.

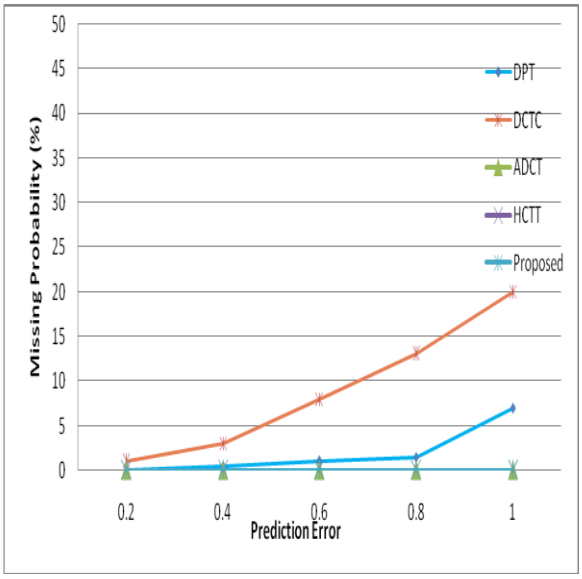


**Fig. 6:** Missing Probability.

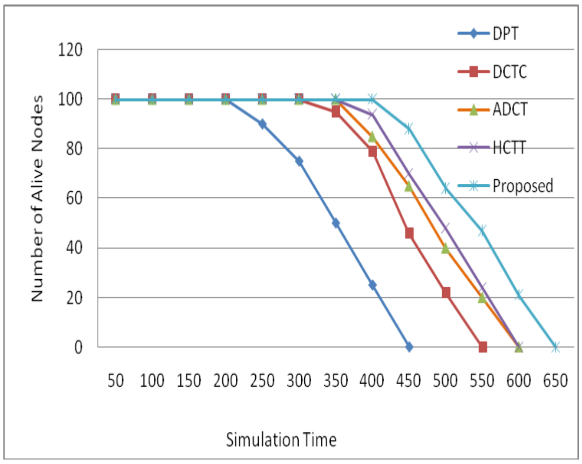


**Fig. 7:** Network Lifetime.

***6. Conclusion:***

Target tracking is an important application of WSNs. Cluster based techniques are proved for its scalability and energy efficiency. However, these suffer the boundary problem when the target moves across or along the boundaries of clusters. If all nodes have to wake up to detect a mobile target, there is a lot of waste of battery power and channel utilization. In our work, we proposed a novel mobility management protocol with low power prediction to reduce the number of nodes participating for target tracking in cluster-based WSNs. Simulation result shows that our method leads to saving energy and thus prolongs the network lifetime regardless of the mobility pattern of the mobile object including Random Waypoint model. The low power predictor used here has lower missing rate than EKF and linear predictors, and the overall network time is extended as compared to existing algorithm. The simulation result demonstrates the efficiency of the proposed protocol in both accuracy of prediction and novelty of mobility management in cluster-based sensor networks

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