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TRUSTWORTHY OPTIMIZED CLUSTERING BASED TARGET DETECTION AND TRACKING FOR WIRELESS SENSOR NETWORK

C. Jehan[1] and D. Shalini Punithavathani[2]
[1]*Department of Computer Science and Engineering, Tamizhan College of Engineering and Technology, India*
E-mail: [1]jehanc2001@gmail.com, [1]cjehan2001@yahoo.com
[2]*Government College of Engineering, Tirunelveli, India*
E-mail: [2]shaliniid50@gmail.com, [2]shalini329@gmail.com

Abstract

In this paper, an efficient approach is proposed to address the problem of target tracking in wireless sensor network (WSN). The problem being tackled here uses adaptive dynamic clustering scheme for tracking the target. It is a specific problem in object tracking. The proposed adaptive dynamic clustering target tracking scheme uses three steps for target tracking. The first step deals with the identification of clusters and cluster heads using OGSAFCM. Here, kernel fuzzy c-means (KFCM) and gravitational search algorithm (GSA) are combined to create clusters. At first, oppositional gravitational search algorithm (OGSA) is used to optimize the initial clustering center and then the KFCM algorithm is availed to guide the classification and the cluster formation process. In the OGSA, the concept of the opposition based population initialization in the basic GSA to improve the convergence profile. The identified clusters are changed dynamically. The second step deals with the data transmission to the cluster heads. The third step deals with the transmission of aggregated data to the base station as well as the detection of target. From the experimental results, the proposed scheme efficiently and efficiently identifies the target. As a result the tracking error is minimized.

Keywords:

Clustering, Dynamic, Target Tracking, Static, Oppositional, Gravitational Search

1. INTRODUCTION

One of the important application of wireless sensor network is target tracking [5] [6] [10]. The main focus of target tracking in WSN is localization and object tracking. For a reliable target tracking system, good tracking quality and energy efficiency are the two very important requirements [1] [3]. In order to save energy as well as to provide good trade off between energy efficiency and tracking accuracy, cluster-based tracking has been preferred for target detection. In cluster tracking system, the nodes are grouped into clusters. The cluster based target tracking can be further divided into two approaches, static clustering and dynamic clustering [2] [12] [14]. In static clustering, clusters are formed statically at the time of network deployment and the clusters are formed before the intruders enter into the network; where as in dynamic clustering clusters are formed dynamically and the clusters are formed by using the signal strength from the target [4] [15] [16] and [21].

In this paper, a fully decentralized Adaptive Dynamic Clustering based Target Tracking scheme has been proposed for single target tracking. The cluster heads are chosen based on the energy levels of the nodes in the cluster. This data is transmitted from all the members of the cluster to the cluster head. Retransmission of data is done on timely manner. The proposed Clustering based Target Tracking scheme has three steps. In the first step, cluster identification and cluster head selection by means of Oppositional Gravitational search optimization (OGSA) with kernel Fuzzy C-means clustering (KFCM) algorithm. Initially, oppositional gravitational search algorithm (OGSA) is utilized to optimize the initial clustering center. Afterwards, the KFCM algorithm is availed to guide the classification and the cluster generation process. The second step, the Cluster Head Data Transmission step deals with the transmission of data from all the members of the cluster to the cluster head within the cluster. The cluster head aggregates all the received data. The third step is the Base Station Tracking step, in which all the cluster heads transmit the aggregated data to the base station. This tracking step detects the target.

The paper proceeds as follows. The section 2 describes the related works and the section 3 explains the network model, WSN formation and GSA algorithm. The section 4 explains the proposed scheme and the section 5 presents the performance evaluation of Adaptive Dynamic Clustering Target Tracking scheme and summarizes the result. Finally, section 6 concludes the paper.

2. LITERATURE REVIEW

A number of approaches have been developed meta-heuristic algorithms to solve various problems in WSNs. Among them, a small number of approaches are discussed in this section.

In [8], the authors propose a location tracking methodology based on radio waves. These employ received signal strength to calculate the location of an object. Their technique basically speaks about selecting a set of points and then based on the RF connectivity between these points; the transmitting sensors are placed only on a subset of 15 these points. The sensors have a limited range of transmission and the observer would receive unique ID packets anywhere in this region. In [9], the author identifies a cluster head which is responsible for implementing the algorithm. In order to minimize traffic and conserve energy, a notification is sent by a sensor to the cluster-head whenever the object is tracked which then queries a subset of sensors to gather more detailed target information. These are intelligent queries based on the cluster-head generating a probability table for each grid point and then subsequent localization if a target is detected by one or more sensors.

The aim of the algorithm in [7] is that every node that has at least one spatial neighbour that is a Delivery-Zone node that will forward or locally broadcast the Mobicast packet. So, all delivery zone nodes will receive the corresponding packet. This simple rule leads an ‘as-soon-as-possible’ style Mobicast protocol that exhibits a high average slack time which is not desirable. The author present self-organized distributed target tracking techniques with prediction based on Pheromones, Bayesian, and Extended Kalman Filter techniques [18], [19]. The implementation and testing of a real distributed sensor network collaborative tracking algorithm in a military context is described in [20].

Sandy Mahfouz et al. [28] described a technique for target tracking in wireless sensor networks. This approach combined machine learning with a Kalman filter to assess instantaneous positions of a moving target. The target's accelerations, along with information from the network, are utilized to achieve an accurate estimation of its position. In [29], they also introduced two major contributions to the wireless sensor network (WSN) society. The first one consists of modeling the relationship between the distances separating sensors and the received signal strength indicators (RSSIs) exchanged by these sensors in an indoor WSN. Vasuhi and Vaidehi [30] have developed a IMM based Target Tracking in WSN named ITTWSN that uses multiple models (velocity and acceleration) to handle both maneuvering and non-maneuvering targets and multiple sensors to detect and identify the targets. The performance of the proposed ITTWSN was compared with the KF scheme and it was found that the accuracy of the proposed ITTWSN was better than the existing KF based approach. Hyunmin Cho and Younggoo Kwon [31] introduced a RSS-based indoor localization algorithm combined with PDR location tracking for wireless sensor networks. The objective was to compensate the NLOS localization error by using PDR, while mitigating the accumulated error of PDR by using RSS-based localization method in LOS conditions.

Cluster based target tracking systems take the advantages of underlying cluster structure evaluated with dynamic clustering protocols, which is particularly appropriate for target tracking in WSNs. Nevertheless, the most widely used algorithms to solve this problem are k-means [24], and fuzzy c-means (FCM) [25]. Bothe algorithms are centroid-based and require a fixed number of clusters beforehand. However, the disadvantages of both algorithms are well known: a correct number of clusters are required beforehand and the algorithms are quite sensitive to centroid initialization [26] [27]. From the above reasons, evolutionary algorithms are shown to be alternative optimization methods using stochastic principles to evolve clustering solutions. Motivated by these studies, an optimized clustering scheme is proposed using oppositional gravitational search and FCM in this paper.

3. METHODS AND MATERIALS

3.1 NETWORK MODEL AND WIRELESS SENSOR NETWORK FORMATION

Wireless sensor network consisting of N nodes is randomly deployed in a uniform distribution over a finite, two-dimensional sensing field with one base station node. The sensor node work collaboratively for target tracking and the base station gathers the data send by all the sensor nodes through the cluster head. To take control of energy management, the energy level and its distance with the cluster head are maintained by the base station. Union of sensing regions of all network nodes guarantees redundant coverage of the region to be supervised and every node has a unique identifier [17].

The wireless sensor network including mobile sensor nodes and a base station is considered [11] [13] and [16]. The base station is considered in our study with the following assumptions. The data transmission between the sensor nodes to the base station is the most important task in the network.

- Diverse energy levels are allocated to all the nodes in the wireless sensor network.
- Every sensor node knows its individual geographical position.
- The sensor nodes measure the environmental parameters at a fixed rate and send the data periodically to the cluster head.
- The nodes exhibit symmetric energy consumption for data transmission.
- In data transmission period, the cluster head performs as the data aggregating node
- Immediately nodes forward the data to the cluster head they move to the wait state and stay on in the sleep mode

3.2 GRAVITATIONAL SEARCH ALGORITHM

Gravitational search algorithm (GSA) is developed based on the law of gravity and motion by Rashedi et al. [23]. In Gravitational search algorithm, each agent (mass) has four significant functions like inertial mass, passive gravitational mass active gravitational mass, and position. The position of the agent (mass) corresponds to the solution of the problem, and its gravitational and inertial masses are computed using a fitness function. The detail explanation of Gravitational search algorithm (GSA) is provided in below:

Update the G, best, worst and M of the population: To derive solution updation process, initially we compute some important parameter like gravitational constant,

$$G(t) = G(G_0, t) = G(t_0) \times \left(\frac{t_0}{t}\right)^A : A < 1 \tag{1}$$

$$G(t) = G_0 \times e^{-\tau\left(iter / iter_{\max} \right)}. \tag{2}$$

Inertial and Gravitational masses are updated using below Eq.(3) and Eq.(4),

$$MS_{acti} = MS_{pasi} = MS_{\text{int}\,i} \text{ for } i = 1, 2, ..., n. \tag{3}$$

To develop the process of GSA, to maintain investigation and utilization by the help of K_{best} agents this will impress the others. K_{best} is an operation of time with the starting value, K_0 and it reduces the time. In such manner, all agents implement the powers at the initial, and as time passes, K_{best} is reduced linearly. Finally, there will be just one agent implementing power to the others and it can be expressed as follows.

$$FRC_i^d(t) = \sum_{j \in K_{best}\, j \neq 1} rand_j \times FRC_{ij}^d(t). \tag{4}$$

In Eq.(4), $rand_j$ is a random number in the interval [0, 1].This random number is utilized to give a randomized characteristic to the search. K_{best} is the set of first K solutions with the best fitness values.

3.2.1 Acceleration Computation:

The acceleration, acc of the solution or agent i at time t in dimension d using the law of motion is provided as in Eq.(5),

$$acc_i^d(t) = \frac{FRC_i^d(t)}{MS_{\text{int}\,i}(t)} \tag{5}$$

where, $MS_{\text{int}i}$ is the inertial mass of i^{th} agent.

3.2.2 Velocity and Position Updation:

Once the accelerator computation is completed, the velocity and position is updated using below in Eq.(6) and Eq.(7).

$$v_i^d(t+1) = rand_i \times v_i^d(t+1) + acc_i^d(t) \tag{6}$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \tag{7}$$

The updated mass i in time t may be stated in Eq.(8) and Eq.(9),

$$ms_i(t) = \frac{fit(t) - worst(t)}{best(t) - worst(t)} \tag{8}$$

$$MS_i(t) = \frac{ms_i(t)}{\sum_{i=1}^{N} ms_i(t)} \tag{9}$$

where, $fit_i(t)$ stand for the fitness value of the i^{th} agent at time t and $best(t)$ and $worst(t)$ are described in Eq.(10) and Eq.(11), respectively for a maximization problem.

$$best(t) = \max_{j \in \{1,\ldots m\}} fit_j(t) \tag{10}$$

$$worst(t) = \min_{j \in \{1,\ldots m\}} fit_j(t) \tag{11}$$

4. PROPOSED ADAPTIVE DYNAMIC CLUSTERING BASED TARGET TRACKING APPROACH

The proposed scheme deals with the assigning of energy levels to nodes, formation of clusters, identification of cluster head, and transmission of data to cluster head and to the base station. Different energy levels are assigned to all the nodes in the network.

The Fig.1 illustrates the flow diagram of the proposed approach. The proposed Adaptive Dynamic Clustering Target Tracking scheme has three steps. The first step the Cluster Formation step deals with the identification of clusters in the network and also the identification of cluster head for each cluster. The clusters are changed dynamically. Within the transmission range of clusters, the cluster head are formed. The second step, the Cluster Head Data Transmission step deals with the transmission of data from all the members of the cluster to the cluster head within the cluster. Once the cluster head is identified for a cluster, the transmission of data takes place from all the other nodes in the cluster to the cluster head.

During data transmission period, the cluster head behaves as the data aggregating node for that particular time interval. As soon as nodes forward the data to the cluster head they move to the wait state and remain in the sleep mode until they have something more to transfer. The reason for remaining in sleep mode is to save energy. The data when aggregated, the energy level of the cluster head gets decremented and the cluster head forwards the aggregated data to the base station. The third step is the Base Station Tracking step, in which all the cluster heads transmit the aggregated data to the base station. This tracking step detects the target using the aggregated data and the information at the base station.

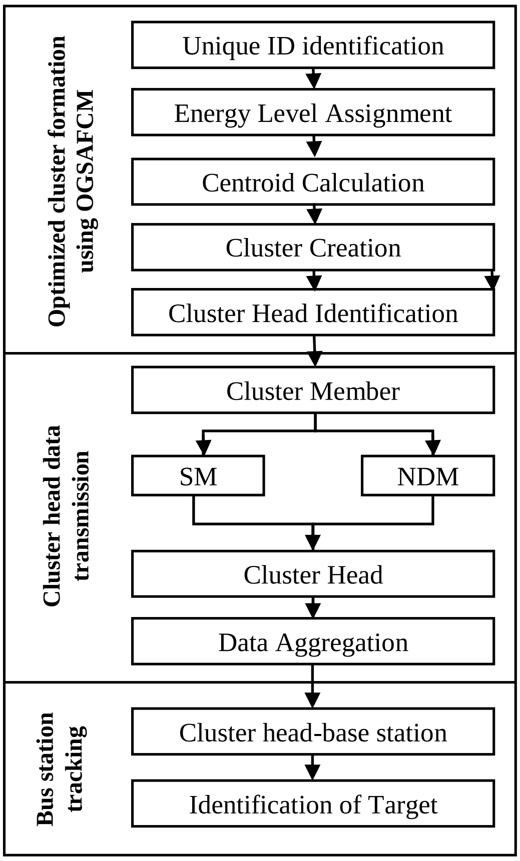

Fig.1. Framework of optimized Dynamic Clustering based Target Tracking Scheme

4.1 CLUSTER FORMATION STEP

Clustering can be used to reduce the amount of data and to induce a categorization. The benefits of clustering are it provides useful energy consumption and scalability for large number of nodes. Clustering also reduces communication overhead. Usually, the cluster members communicate with the cluster head and the gathered data are aggregated and combined by the cluster head to conserve energy. In addition, the cluster heads can create another layer of clusters between themselves before attaining the base station.

In the sensor network, unique identification and energy level assignment process is assigned on each node. After that, cluster creation and cluster head identification is computed using optimized FCM. In clustering process, N nodes into m clusters are created using oppositional gravitational search optimization (OGSA) based fuzzy clustering to cluster formation efficiently. At first, the opposition learning based gravitational search algorithm is used to optimize the initial clustering center. The key idea opposition process is the simultaneous consideration of an estimate and its corresponding opposite estimate in order to obtain better approximation. After that, Kernel Fuzzy C-means algorithm (KFCM) is availed to guide the categorization, so as to improve the clustering performance of the FCM algorithm. During cluster formation several parameters such as the distance to the base station, the cluster distance and the dissipated energy are also calculated simultaneously.

Fitness computation: To evaluate the each agent or individuals, we use a fitness function. Fitness function is the relationship between an agent and its fitness. Fitness function is given below in Eq.(12), Eq.(13) and Eq.(14),

$$f(U,V)=\frac{1}{1+J_{KFCM}(U,V)} \tag{12}$$

$$=\frac{1}{1+\sum_{k=1}^{c}\sum_{i=1}^{n}\mu_{ki}^{m}\left|\phi(x_k)-\phi(v_i)\right|^2} \tag{13}$$

$$=\frac{1}{1+\sum_{k=1}^{c}\sum_{i=1}^{n}\mu_{ki}^{m}\left(2-2K(x_k,v_i)\right)} \tag{14}$$

where, $K(x_k,v_i)=\exp\left(\frac{-\left|x_k-v_i\right|^2}{\tau^2}\right)$.

The detail explanation of OGSAFCM algorithm is presented below:

Algorithm 1: OGSAFCM Algorithm

Step 1: Begin

Step 2: Initialize: Set the parameters of KFCM approach, c, t_{max}, $m > 1$, $\varepsilon > 0$ for some positive constant.

Step 3: Set the parameters of OGSAFCM algorithm, iterations T, opposition population initialization OP_0.

for ($i = 0$; $i < M_p$; i++) // M_p: Population size

for ($j = 0$; $j < d$; j++) //d: problem definition

$$OP_{0_{i,j}} = p_j + q_j - P_{0_{i,j}}$$

Select N_p fittest agents from set of $\{P_0, OP_0\}$as initial population

End of opposition population initialization

Step 4: Compute J_{KFCM} (U,V) of each agent in the population, and the fitness of each agent $f(U,V)$

Step 5: Compute the fitness $\overline{f(U,V)}=\frac{1}{n}\sum_{k=1}^{n}f(k)$,

if $\left|\overline{f(t)}-\overline{f(t+1)}\right|>\delta$,

else $t = t + 1$, go to step 3

Step 6: Update $G(t)$, $M_i(t)$, $best(t)$ and $worst(t)$ for $i = 1,2,..,n$

Step 7: Computation of the total forces in diverse directions

Step 8: Computation of accelerations and velocities

Step 9: Updation of agent positions using Eq.(7)

Step 10: Choose the best agent of the last generation as the algorithm's final results;

Step 11: End

4.2 CLUSTER HEAD DATA TRANSMISSION STEP

A node in the network can be identified either as a cluster head ξh or as a cluster member ζm. The members of the cluster are known as the cluster member and the centroid is known as the cluster head. After cluster formation the data such as energy level of each cluster member and its Euclidean distance to the centroid are transmitted to the cluster head. The cluster members generally communicate with the cluster head for the transmission of data. The members of the formed cluster ζm can communicate with their ξh directly. A cluster head ξh can forward the aggregated data to the base station through other ξh. A cluster member passes the data to the cluster head based on two measures: Straight Measure SM and Non-Direct Measure NDM.

In SM, a cluster member ζm transfers the data directly to its cluster head ξh without any intermediate members. In SM the cluster members has direct link with its head so that the data can be transmitted surely and the energy consumption is low, resulting in the saving of energy. After the transmission of data, the cluster member turns to the wait state resulting in sleep mode.

In NDM, a cluster member ζm does not transfer the data directly to its cluster head ξh, but transfer through it an intermediate member. In NDM, the cluster members has no direct link with its head, the data has to be transmitted through another neighbour member of its cluster. After transmitting the data, both the cluster members turn to wait state resulting in sleep mode.

The Cluster Head Data Transmission using NDM and SM measures is explained in Fig.2. The Fig.2 explains how data are transmitted to the cluster head. The NDM measure shows the cooperation between two cluster members. When a node A wants to send data to the cluster head ξh it cannot transmit directly, it can transmit only through the node B. Node A then hear from node B whether it will transmit the forwarded data to the cluster head. After getting proper response from node B, now node A is ready to send the data to node B. Now node A transfer its data to node B, node B after receiving it transfer the data to the cluster head. Non direct measure also occurs between nodes D and E, whereas node C and node F can directly send the data to the cluster head using single measure.

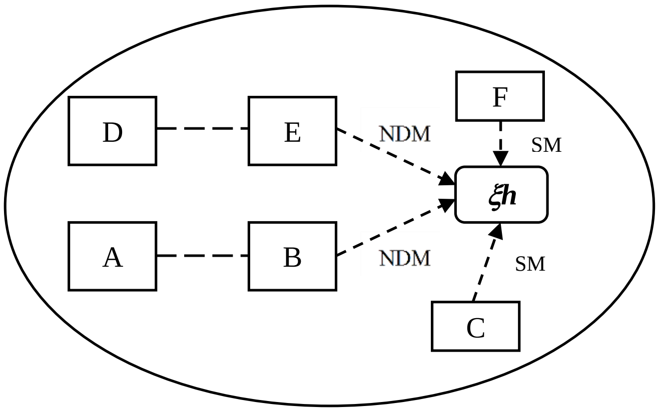

Fig.2. Cluster Head Data Transmission using NDM and SM measure

The cluster head aggregates all the data received from all the cluster members of its cluster. Let there be s cluster members in a cluster. The s data from s members are aggregated at the cluster head. The members are represented as ζm_1, ζm_2 - - - - ζm_s. The data of the members are represented as ζmd_1, ζmd_2 - - - - ζmd_s.

The first two cluster member data are aggregated as in Eq.(15), the first ζmd_1 and the second ζmd_2, where x_1 is the weight of first data member data and x_2 is the weight of the second member data. Likewise all the cluster member data are aggregated to obtain the aggregated-data value λ_s for s cluster members.

$$\lambda_S = \left[\left(x_1 \times \xi md_1 + x_2 \times \xi md_2\right)\right],\ i \in \{1, s\} \tag{15}$$

4.3 BASE STATION TRACKING STEP

The cluster heads after obtaining the aggregated data members generally communicate with the base station. All the cluster heads ξh communicate with the base station directly or can forward the aggregated data to the base station through intermediate cluster head ξh. A cluster head passes the aggregated data to the base station either directly or by intermediate cluster head.

Under direct method, a cluster head ξh transfer the data directly to the base station without any intermediate members. In this method, cluster head has direct link with the base station so that aggregated data can be transmitted safely and the energy consumption is low resulting in the saving of energy. After transmitting the aggregated data the cluster head turns to wait state resulting in sleep mode.

In indirect method, the cluster head ξh do not transfer the data directly to the base station using intermediate cluster head, but transfer through an intermediate cluster head, because it is not in one hop transmission. In this scheme the cluster head has no direct link with the base station so that the aggregated data has to be transmitted only through another neighbour cluster head. After transmitting the data, both the cluster head will turn to wait state resulting in sleep mode. Using the aggregated data send by the cluster head, the base station BS identifies the target efficiently. As the base station BS efficiently detects the target using the relative information of the base station BS, the targeting error is minimized. The Adaptive Dynamic Clustering Target Tracking Scheme is explained in Algorithm 2.

Algorithm 2: Adaptive Dynamic Clustering Target Tracking Scheme
1. for $\forall$ nodes 1 to N
2. Identify $m \rightarrow C_d$
3. $\forall N \rightarrow C_d : \Rightarrow E_d$
4. Identify Cluster C_i using section 4.1
5. End for
6. for i = 1 to m
7. $\xi h_i \leftarrow C_i$
8. $\xi hi \leftarrow \{\zeta md_1, \zeta md_2 - - - - \zeta md_s\} \Leftarrow \{\zeta m_1, \zeta m_2 - - - - \zeta m_s\}$
9. $\lambda_s = \left\lceil \left(x_1 \times \zeta md_1 + x_2 \times \zeta md_2\right) \right\rceil$, $i \in \{1, s\}$
10. BS $\leftarrow \{\xi h_1, \xi h_2, \xi h_3$ - - - - $\xi h_m\}$
11. Identify target
12. End for

5. SIMULATION RESULTS AND DISCUSSION

The target tracking clustering algorithm was implemented using the Network Stimulator-2. The total numbers of clusters are generated dynamically in order to maintain the energy level to minimum. The sensor network with 100 nodes is deployment in a 15×15 matrix and they are separated by 30m.

We employ the following metrics to evaluate the performance of our proposed approach:

i) Number of dynamic clusters: The number of dynamic clusters generated during the target tracking process.

ii) Missing probability: It means that the probability of missing the target as a target moves in the network.

iii) Tracking error (Prediction): the distance difference between the estimated location computed by the system and the real location of the target.

iv) Energy dissipated: The energy consumed for target tracking process.

5.1 PERFORMANCE EVALUATION

5.1.1 Simulation on Cluster Formation:

The Fig.3 shows the performance of optimized cluster creation process. In this section, we wanted to compare our OGSAFCM against existing implementation clustering methods like GSAFCM, GAFCM, original FCM and K-means algorithms. Analyzing these result, our proposed approach of OGSAFCM achieved better performance than other methods.

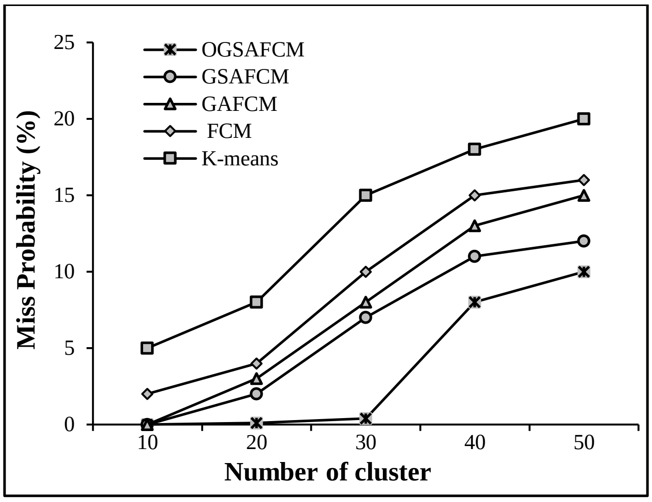

Fig.3. Miss Probability versus cluster size for different clustering algorithms

The Fig.4 illustrates the variation of the number of clusters with the node degree. As the number of node degree increases, the number of clusters decreases. It is also noted that as the number of network nodes increases the cluster count also increases. The cluster count is increased maximum up to the count of number of nodes for lower node degrees. It is observed that as the node degree increases beyond the node count it becomes almost zero. In this simulation, the number of clusters and the node degree are compared for four different node counts 20, 40, 60 and 80.

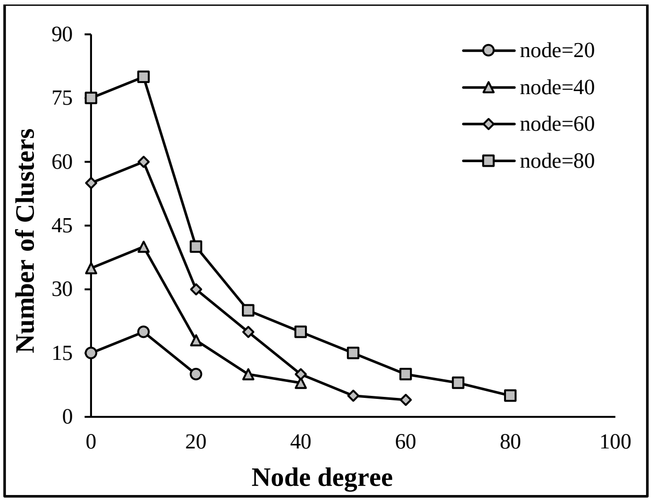

Fig.4. Variation of number of clusters for different network size with increasing node degree

5.1.2 Tracking Error:

The Fig.5 illustrates the variation of tracking error with time period for varying time ratio Ot/Tp. The time ratio (Ot/Tp) is the ratio of the on-time to the time period. For the time ratio Ot/Tp, the average tracking error increases with the time period. As the time period increases, the tracking error also increases. The tracking error is low for higher time ratio than lower time ratio. In this simulation, four time ratios of 0.1, 0.2, 0.3 and 0.4 are discussed. The tracking error is low for 0.4 time ratio compared to the other ratios. For 0.4 time ratio the tracking error is 8 for tenth time period, whereas it is low for lesser time period.

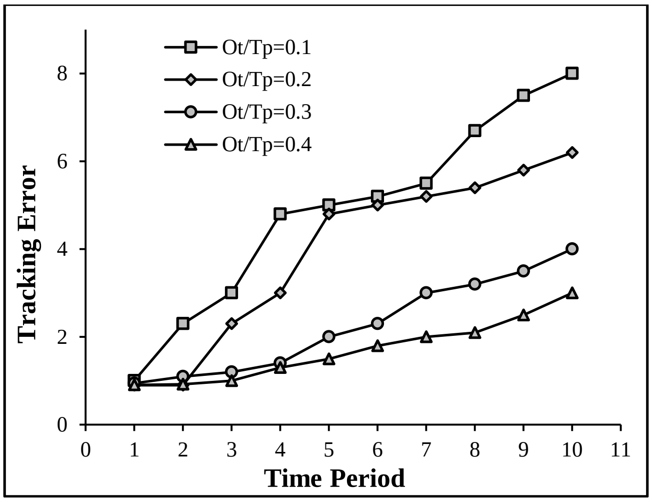

Fig.5. Simulation on tracking error for varying time ratio for increasing time period

5.1.3 Energy Dissipation:

The Fig.6 illustrates the variation of energy dissipation for varying cluster size for increasing time period. Energy dissipation represents the amount of energy dissipated for the formation of clusters. The simulation represents the energy dissipation for four different cluster size C_i of 10, 20, 30 and 40. As the number of clusters increases, the energy dissipated increases for increasing time period. The energy dissipation is higher for the cluster size of 40 when compared to the other cluster sizes.

5.2 COMPARATIVE ANALYSIS

In this section, we provide a comparative analysis to prove the effectiveness of our proposed system. The results obtained from the proposed approach are compared with other published research method (Zhibo Wang et al. [22]). In [22], they have developed a hybrid cluster-based Target tracking Protocol for Wireless Sensor Networks.

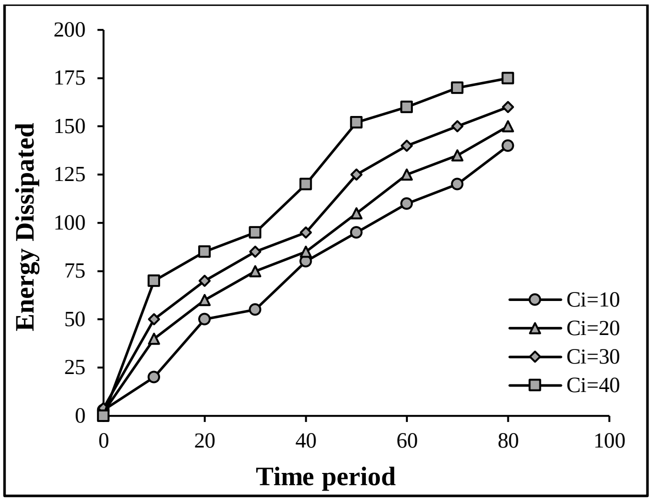

Fig.6. Simulation on energy dissipation for varying cluster size for increasing time period

5.2.1 Miss Probability:

The Fig.7 shows the performance of the missing probability versus cluster size. We can see that the missing probability of Zhibo Wang et al. [22] drops slightly when the cluster size increases from 10 to 60. This is because that it is more likely to make wrong tracking predictions when vary the cluster size. But proposed method achieves better predictions than existing system. This validates that the optimized based clustering based approach can solve the target problem efficiently.

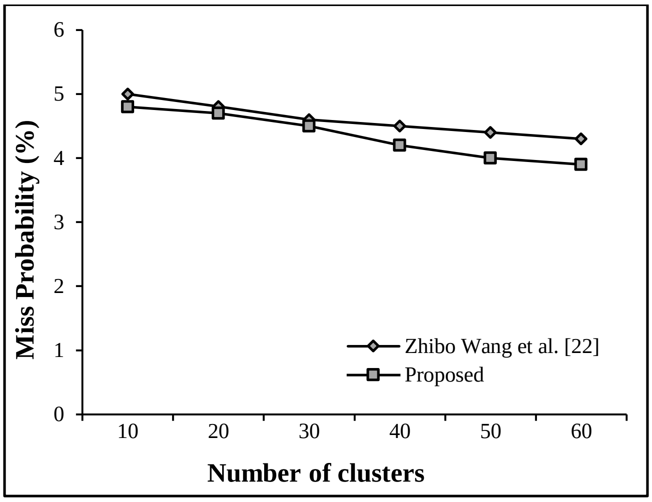

Fig.7. Missing Probability versus Cluster Sizes

The Fig.8 illustrates the effect of the tracking error (prediction error) on the missing probabilities of proposed and existing approaches. We can see that the missing probability of proposed approach is achieved in terms of tracking error (prediction error) than the existing method. For that reason, the tracking error has no effect on the performance of proposed approach.

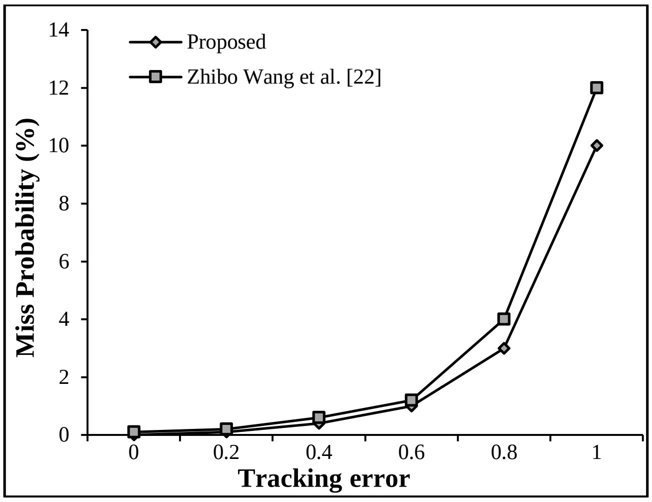

Fig.8. Missing Probability versus Tracking Error

6. CONCLUSION

In this paper, en efficient clustering based target tracking in wireless sensor network was proposed combining Oppositional GSA and FCM clustering. An optimized clustering scheme was used for the formation of clusters. The cluster creation allows the network to enjoy the right of energy consumption resulting in the saving of energy. The proposed Trustworthy Adaptive Dynamic Clustering Target Tracking scheme used three steps for tracking of target. The first step, the cluster formation step deals with the cluster formation and the identification of cluster head dynamically for each cluster. The second step, the cluster head data transmission step deals with the transmission of data. The third is the base station tracking step which transmits the aggregated data to the base station. This tracking step detects the target and sends the relative information of the target. The proposed scheme efficiently and efficiently identifies the target. From the experimental results, the tracking error is minimized compare with existing methods.

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