Dynamic Cluster Head Selection in Wireless Sensor Network for Internet of Things Applications

Aniji John, Anagha Rajput
Department of Communication Engineering,
VIT University,
Vellore, India.
anijijohn@gmail.com, anagharajput@gmail.com

Vinoth Babu K
Department of Communication Engineering,
VIT University,
Vellore, India.
vinothbab@gmail.com

***Abstract*-Internet of things (IoT) integrate the technologies such as sensing, communication, networking and cloud computing in wide range monitoring zone. For applications of IoT, the most appropriate monitoring network is wireless sensor networks (WSN). It is most important to develop energy efficient cluster head (CH) selection scheme to increase the network lifetime of WSNs. It is most crucial to save the energy of these sensor nodes to avoid quick battery drain. In this work, a dynamic CH selection method (DCHSM) is proposed to extend the network lifetime of the systems developed for IoT applications. At first the concept of Voronoi diagram is utilized to divide the large scale monitoring area into small clusters in order to ensure maximum coverage and then the CH is selected in two stages. The first stage of the CH selection is based on perceived probability and the second stage is based on the survival time estimation. Results depicts that the new work performs better than existing algorithms with regard to energy saving and network lifetime for the IoT systems.**

Keywords—Cluster Head (CH), Dynamic Cluster Head Selection Method (DCHSM), Internet of Things (IoT), Voronoi Diagram, Wireless Sensor Network (WSN)

I. INTRODUCTION

Recently internet is growing rapidly towards the combining sensors and devices on internet, which is described as IoT systems [1]. A system supporting IoT integrates sensing, networking, communication, also cloud computing techniques. WSNs are the most powerful networking infrastructure that monitors an IoT system [2,3]. WSNs play crucial role in IoT by collecting the physical data in large scale. These information's are used in applications like intelligent transportation systems, battlefield surveillance systems, health care systems, industrial control, environment monitoring etc. Further, WSN supports IoT to meet the challenges of scalability and energy efficiency since self-organizing sensor nodes with limited energy are utilized for large scale data collection.

A WSN consists of thousands of sensing nodes. The sensor nodes, which have scarcity of resource are deployed into a dense and unknown environment without any predefined infrastructure. Initially the sensor nodes deploy themselves to the working environment and then start monitoring the area. The sensor nodes, which are designed with low power consumption and low cost, self-organize themselves into a network. Moreover, the monitoring demand of the large scale environment of IoT systems cannot be met, if few nodes do not work efficiently. Energy consumption should be considered to extend the network lifetime of IoT systems. Energy saving is an important feature of WSN. Sensors spent most of their energy during transmitting and receiving messages. Battery acts as the main power supply of sensor nodes. In IoT applications, hundreds or thousands of sensor nodes are placed in dense geographical environment. The sensor nodes are usually deployed in the locations where the users are difficult to reach. It is impossible to replace the batteries of this large number of sensor nodes which are deployed in areas out of reach of users. In order to avoid quick battery drain, energy saving of sensor nodes is to be taken care. Thus efficient energy saving scheme should be deployed.

Researches in WSN were done on energy saving issues [4,5]. It is possible to effectively reduce the energy consumption of the network by organizing sensor nodes in the form of clusters. One of the methods to minimize energy consumption in WSN is cluster based technique. Once the nodes are categorized into clusters, CHs and cluster members (non CHs) are identified. The non CH member is responsible only to look after the sensing area. CH collects the information from all the non CHs in its cluster. After this, the data is processed and send to the base station (BS). Since only CHs sent data to BS directly, the distance of data transmission is minimized, due to which the energy consumption is reduced in WSN. Improper CH selection may lead to inefficient energy consumption. The cluster based techniques can be classified into distributed clustering approach and centralized clustering approach.

In the former algorithm, the clustering become distributed, where each node decide its actions and tasks itself [6]. The major problem of this technique is the non-uniform cluster size. In such cases, some clusters contain more nodes and few nodes might need to spent more energy for passing the sensed data to BS, since BS is located far away. Due to this problem, the expected energy balancing might not be achieved. In centralized, BS takes the initiative to communicate with the BS about all the activities regarding clustering in the network. In centralized approaches better energy saving can be achieved. But when it comes to large scale networks, the problem comes in the form of scalability. BS finds difficult to monitor the activities of all the deployed nodes. The centralized techniques are suitable only for small scale networks with less number of sensor nodes. It is a failure for large scale WSN in applications of IoT systems. Until now, the researchers are not happy about energy saving and the stability of WSNs. Low energy adaptive clustering hierarchy (LEACH) algorithm uses distributed clustering [7]. CH for each cluster is selected based on predetermined probability. Non CH nodes choose the nearest cluster to which it should join considering the link quality. In order to improve the network lifetime the CH selection process of LEACH is improved and named E-LEACH, which concentrates on leftover energy of each node [8]. Another energy efficient clustering protocol named distributed energy efficient clustering (DEEC) is developed for the characteristics of heterogeneous WSNs [9].

Dynamic clustering based WSN is used in IoT applications, where the idea of CH rotation is utilized in-order to maintain the data traffic among nodes [10]. Dynamic clustering has attracted various research communities due to its advantages of energy saving and scalability.

In this work, a DCHSM is proposed for CH selection. At first, the clustering area is divided with the help of Voronoi diagram, then the first kind of CH nodes are selected with the help of perceived probability model. After the death of first kind of nodes, the second kind of nodes are selected with the help survival time estimation algorithm in which the proportion of the residual energy to average energy of the network nodes are considered.

The work is organized as follows: The first stage of CH selection is explained in section II. The second stage of CH selection is explained in section III. Simulation analysis is given in section IV. Finally conclusion can be observed from section V.

II. STAGE 1- CH SELECTION BASED ON PERCEIVED PROBABILITY

Consider a two dimensional rectangular region. Assume that the BS is located at its center. The nodes are placed randomly [11,12]. At first, the monitoring area is divided into polygons using Voronoi diagram shown in Fig.1. After dividing the monitoring area into polygonal mesh, choose the node whose sensing field is covered by the other nodes in each mesh as active nodes. The remaining nodes will go to sleep mode. In each Voronoi polygon, the distance between the active node and the remaining node is expected to be minimum. The sensing radius of sensor nodes is denoted by r and it is considered to have a value greater than communication radius.

A circular area centered by a node which has n_i sensor nodes and the sensing radius r is called as the sensing range. Let $c(l_j, m_j)$ denotes the coordinate of each point c in the monitoring area and $n_i(l_i, m_i)$ represents the coordinate of each sensor node. The variable s denotes the distance from each node n_i to the target point c and is given by

$$s(n_i, c) = \sqrt{(l_i - l_j)^2 + (m_i - m_j)^2} \quad (1)$$

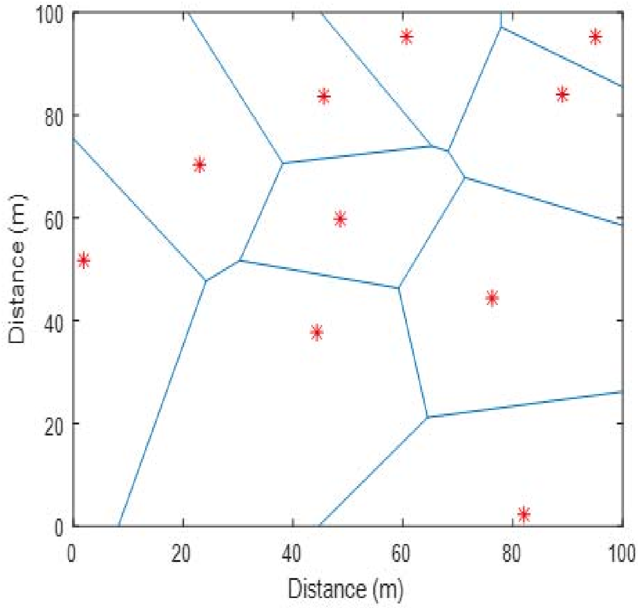

Figure 1. Cluster formation based on Voronoi diagram

Perceptual probability model of each node n_i to each c is

$$P(n_i, c) = \begin{cases} 1 & ; s(n_i, c) < r - a \\ e^{-\alpha s_i} & ; r - a \le s(n_i, c) < r + a \\ 0 & ; s(n_i, c) \ge r + a \end{cases} \quad (2)$$

$$s_i = s(n_i, c) - (r - a) \quad (3)$$

The distance s_i plays important role, since the condition for attaining probability of each node is formulated depending on these distances. α is the parameter related to the monitoring of physical device and a is the uncertainty value in monitoring of sensor nodes. Also, the probability value should be greater than the threshold value of perceived probability T_{min}

$$P(n_i, c) \ge T_{min} \quad (4)$$

The other M sensor nodes in the area can simultaneously perceive its respective target point c. The node public perception of c is obtained using

$$w(c) = \sum_{i=1}^{M} P(n_i, c) = \sum_{i=1}^{M} e^{-\alpha s_i} \quad (5)$$

The network perception contribution of each sensor node to the nodes in the whole monitoring area is given by

$$y(n_i, c) = \frac{P(n_i, c)}{w(c)} \quad (6)$$

Finally the node which gives the minimum value of $y(n_i, c)$ is chosen as the CH.

III. STAGE 2- CH SELECTION BASED ON SURVIVAL TIME ESTIMATION

After the death of first kind of CH nodes, select another kind of CH nodes from remaining nodes, considering proportion of the remaining energy of nodes, also average remaining energy of the network. To achieve prolonged network lifetime, one with higher residual energy become CH. The following equation denotes the probability of remaining nodes to become CH node

$$p_i = p\left[1 - \frac{\overline{J(f)} - J(f)}{\overline{J(f)}}\right] \quad (7)$$

here $$\overline{J(f)} = \frac{1}{M}\sum_{i=1}^{M} J_i(f) \quad (8)$$

where p is the optimum number of CH nodes, $J_i(f)$ denotes the residual energy of each sensor node in the f^{th} round. $\overline{J(f)}$ represents the average residual energy of the network.

The total number of rounds i.e. lifetime of the network is calculated using

$$L = \frac{J_{tot}}{J_{round}} \quad (9)$$

where J_{tot} is the total energy of the network during the initial stage. J_{round} represents the amount of energy consumed by the system in every round, which is given by

$$J_{round} = b(2MJ_{comp} + MJ_{da} + \tau\gamma_{amp}\, s_{CH-BS}^4 + M\tau\gamma_{fs}\, s_{nonCH-CH}^2) \quad (10)$$

where τ is total CH nodes count in the network, b represents packet size, J_{comp} represents the energy utilized to run the the electronic circuits, J_{da} denotes the energy consumed during the process of data aggression, γ_{amp} and γ_{fs} denotes the transistor amplifier characteristics, s_{CH-BS} denotes the average distance joining BS and CHs, $s_{nonCH-CH}$ is average distance joining CHs and non CHs, given by

$$s_{nonCH-CH} = \frac{A}{\sqrt{2\pi\tau}} \quad (11)$$

where $\frac{A}{\sqrt{\pi\tau}}$ denotes the radius of the circular area considered to calculate the expected square distance from non CH nodes to CH. The optimum count of CH nodes is obtained when the derivative of J_{round} is taken with τ and equating it with zero. It is given by

$$\tau = \sqrt{\frac{M\gamma_{fs}}{2\pi\gamma_{amp}}} * \frac{A}{s_{nonCH-CH}} \quad (12)$$

Thus, uniform energy distribution is maintained by choosing the second kind of CH node by considering the proportion of residual energy of nodes to average residual energy of network.

IV. SIMULATION ANALYSIS

We have considered a 100 X 100 square meter monitoring zone. After partitioning observing zone, the sensor nodes are deployed manually using graphical inputs as displayed in Fig. 2. The simulation is performed using MATLAB 2015a tool. The simulation parameters are listed in Table 1. Polygonal clusters formed using Voronoi diagram partition the monitoring area uniformly. Here cluster formation gives mean point directly, which reduces complexity of algorithm.

TABLE I
VARIABLES USED IN WORK

Variable	Value
Electronics energy (J_{comp})	50 nJ / bit
Energy- data aggression (J_{da})	5 pJ / bit / message
Initial energy of each node (J_{init})	0.5 J
Communication energy (γ_{amp}) for two ray ground reflection model	0.0013 pJ / bit / m^4
Communication energy (γ_{fs}) for free space propagation model	10 pJ / bit / m^2
Packet size (b)	2000 bits
Threshold value of distance (d_0)	70 m
Threshold distance of perceived probability (T_{min})	0.3
Sensing area (M X M)	100 X 100
Position of BS (50, 175)	(50,175)
Number of nodes	100

The proposed algorithm is simulated in two stages. First stage of CH selection is based on perceived probability considering the distances of each sensor node with respect to the respective mean point in its cluster. The sensor node located near to mean point of the cluster is selected as CH. In contrast to DCHSM, in conventional LEACH algorithm, the CH selection is based only on the comparison of random number generated and threshold value. After the death of first kind of CH nodes, second stage of CH selection is performed using survival time estimation algorithm. It relies on the proportion of remaining energy of sensor nodes to average network energy.

Fair comparison between DCHSM and conventional LEACH algorithm is displayed in Fig. 3. The residual energy of the network is plotted for many number of rounds. Simulation results show that energy saving is improved in DCHSM when compared to conventional LEACH algorithm. After the death of first stage of CH, the energy saving is improved by 8.12 % using DCHSM, which increases the network lifetime. Furthermore, even after when LEACH network dies, DCHSM is still alive with 10 % energy being saved. Using DCHSM algorithm, the network continue to function for more number of rounds.

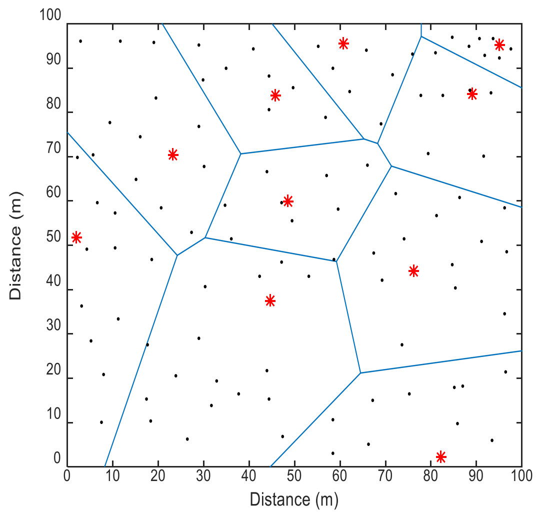

Figure 2. Nodes deployed in Voronoi diagram

V. CONCLUSION

In this work, we have tested the performance of DCHSM in WSN. After generating clusters with the help of Voronoi diagram the CHs are selected in two stages. The first stage is based on perceived probability and the second stage is based on survival time estimation. Based on the study, we can conclude, DCHSM improves energy saving in WSN by about 8.12 % when compared to LEACH and thereby increases network lifetime. The simulation is proved to give better results for less nodes. In future this work can be tested for thousands of nodes. Moreover, simple energy models are used which are not practically applicable.

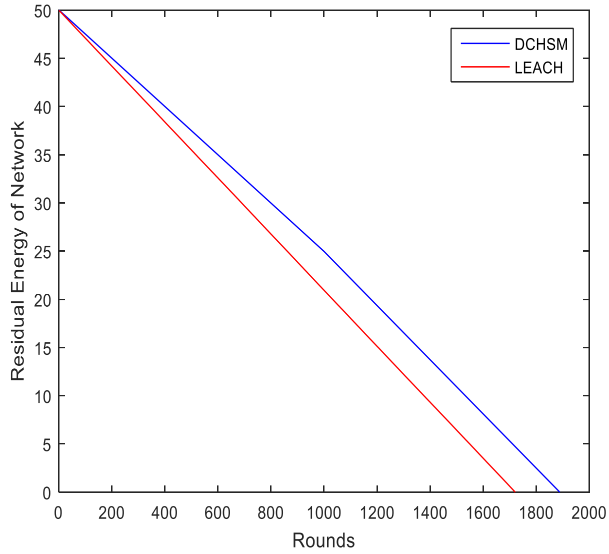

Figure 3. Residual energy of network Vs. Rounds

References

[1] Atzori, L., Iera, A., and Morabito, G, "The internet of things: A survey. Computer Networks," vol. 54, pp. 2787–2805, 2010.

[2] Zhezhuang Xu, Liquan Chen, Cailian Chen and Xinping Guan, "Joint Clustering and Routing Design for Reliable and Efficient Data Collection in Large-Scale Wireless Sensor Networks," IEEE Internet of Things J., vol. 3, no. 4, August 2016.

[3] Al-Karaki, J. N., and Kamal, A. E, "Routing techniques in wireless sensor networks: A survey. IEEE Wireless Communications," vol. 11, pp. 6–28, 2004.

[4] Chamam, A, and Pierre, S, "On the planning of wireless sensor networks: Energy-efficient clustering under the joint routing and coverage constraint," IEEE Trans. on Mobile Computing, vol. 8, pp. 1078– 1086, 2009.

[5] S.K.Singh, M. P. Singh, and D. K. Singh, "A survey of energy-efficient hierarchical cluster-based routing in wireless sensor networks," International J. of Advanced Networking and Application (IJANA), pp. 570-580, 2010.

[6] Jau-Yang Chang, "A Distributed Cluster Computing Energy-Efficient Routing Scheme for Internet Of Things Systems," Wireless Pers Commun, Springer Sceince+Business Media, New York, 2015.

[7] S. Tyagi and N. Kumar, "A systematic review on clustering and Routing techniques based upon LEACH protocol for wireless sensor networks," J. Netw. Comput. Appl., vol. 36, no. 2, pp. 623–645, Mar. 2013.

[8] Handy, M. J, Marc Haase, and Dirk Timmermann, "Low energy adaptive clustering hierarchy with deterministic cluster-head selection," Mobile and Wireless Communications Network, 4th International Workshop on IEEE, 2002.

[9] Qing, Li, Qingxin Zhu, and Mingwen Wang, "Design of a distributed energy-efficient clustering algorithm for heterogeneous wireless sensor networks," Computer communications, vol. 29, no.12, pp. 2230-2237, 2006.

[10] Dongyao Jia, Huaihua Zhu, Shengxiong Zou, and Po Hu, "Dynamic Cluster Head Selection Method for Wireless Sensor Network," IEEE Sensors J., vol. 16, no. 8, April 15, 2016.

[11] Gavrilova, Marina L., ed, " Generalized voronoi diagram: a geometry-based approach to computational intelligence," vol. 158. Springer, October 2008.

[12] A. Franz, R. Klein et al, "Voronoi diagrams and Delaunay triangulations," vol. 8. Singapore: World Scientific, 2013.