American Journal of Sensor Technology, 2014, Vol. 2, No. 1, 1-6
Available online at http://pubs.sciepub.com/ajst/2/1/1

DOI:10.12691/ajst-2-1-1

A Low Energy Time Based Clustering Technique for Routing in Wireless Sensor Networks

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Received August 11, 2013; Revised November 05, 2013; Accepted January 24, 2014

Abstract A Wireless sensor network (WSN) is a collection of tiny sensor nodes that are deployed to monitor the environment. These sensor nodes have limited capabilities, especially the energy reserve and processing ability. So, the routing protocols design for this kind of networks is a crucial challenge. Because these routing protocols should be simple, energy-efficient, and robust to deal with a very large number of nodes, they should also be self-configurable to node failures and changes of the network topology dynamically. The most proposed routing techniques organize the network in clusters where the sensing area is divided into many sub-areas. This paper presents a new algorithm for clustering in WSN based on the node residual energy compared to the network one and allowing a better partitioning of the network area which enhance the data distortion at the sink by using the best data coding rate at the cluster head. The simulation results show that this algorithm allows network stability extension compared to the most known clustering algorithm.

Keywords: *wireless sensor networks, energy efficiency, clustering-based algorithm, data aggregation, data compression*

Cite This Article: Ouadoudi Zytoune, and Driss Aboutajdine, "A Low Energy Time Based Clustering Technique for Routing in Wireless Sensor Networks." *American Journal of Sensor Technology*, vol. 2, no. 1 (2014): 1-6. doi: 10.12691/ajst-2-1-1.

1. Introduction

A Wireless Sensor Network (WSN) is a collection of tiny and lightweight sensor nodes deployed in large numbers to monitor the surrounding conditions [1]. They have diverse application domains: environmental survey, smart home, medical monitoring, agriculture etc.

Since they have small size, the available energy at each sensor nodes is considered as the major constraint. Hence energy consumption is the important criteria for designing of this kind of networks [2,3]. Some of the early works on WSNs have discussed the benefits of WSNs in detail [4,5,6]. As main advantages of WSNs over the conventional networks deployed for the same purpose we can cite greater coverage, accuracy, reliability and all of the above at a possibly lower cost.

Clustering is the process of partitioning a network into groups of sensor nodes called clusters. Each cluster consists of nodes member and one or more number of cluster heads (CH) [7]. The CH gathers all data from their cluster members. The collected information is routed to the Base Station (BS). Generally, the BS is a fixed node, which is capable to transmit and receive the data within the entire network [8]. The number of cluster head selection depends on the number of sensor nodes and the network topology. Selecting more than one CH for cluster containing more number of nodes in the network can control the energy consumption efficiency [6,9].

Even if clusters formation and maintenance inducts additional cost due to the control messages needed for this purpose, still cluster-based WSNs have taken much attention of the researchers due to their better performance. Distributed, dynamic and randomized clustering schemes are interesting due to their simplicity, feasibility, and effectiveness in providing energy-efficient utilization, load balancing and scalability simultaneously [10].

And then many research projects in the last few years have explored hierarchical clustering in WSN from different perspectives. A variety of protocols have been proposed for prolonging the life of WSN and for routing the correct data to the BS. Each protocol has advantages and disadvantages. Some of the hierarchical protocols are LEACH (Low-Energy Adaptive Clustering Hierarchy) [11,12], PEGASIS (Power-Efficient Gathering in Sensor Information Systems) [13], TEEN (Threshold sensitive Energy Efficient sensor Network protocol) [14,15], SEP(Stable Election Protocol for clustered heterogeneous wireless sensor networks) [16], DEEC(Distributed Energy Efficient Clustering algorithm for heterogeneous wireless sensor networks) [17] and APTEEN(Adaptive Periodic Threshold-sensitive Energy Efficient sensor network protocol) [18].

In this paper we present a new technique for network clustering in order to extend the network lifetime and to enhance the data correlation. The main object is to equitably distribute the cluster heads among the network nodes. The remainder of the paper is arranged as follows. Section-2 provides the background about cluster-based routing protocol for WSNs. The details of the proposed technique have been discussed in section-3. Simulation parameters and results have been given in section-4. Based upon the simulation results, conclusions have been drawn and some recommendations for future work have been proposed in section-5.

2. Related Work

Because of many WSN applications require only an aggregate value to be reported to the observer, sensors in different regions of the monitored field can collaborate to aggregate their data and provide more accurate reports about their local regions. For example, in a habitat monitoring application [19], the average reported humidity values might be sufficient for the observer. In military fields where chemical activity or radiation is measured, the maximum value may be required to alert the troops. By reason of the large part of the WSN energy is consumed in wireless communication, several communication protocols have been proposed to realize power-efficient communication. Clustering technique is the main schemes used to route information in WSNs. In addition to improving the fidelity of the reported measurements, data aggregation reduces the communication overhead in the network, leading to significant energy savings. In order to support data aggregation through efficient network organization, nodes can be partitioned into a number of small groups called clusters.

Figure 1 gives the cluster organization. When an event occurs, each node in its vicinity sends its reading (the collected data) to their cluster head that performs data aggregation and sends it to the sink. Because of data correlation decreases when the sensor is far from the event, the collected data at the sink may be altered as has been explained above.

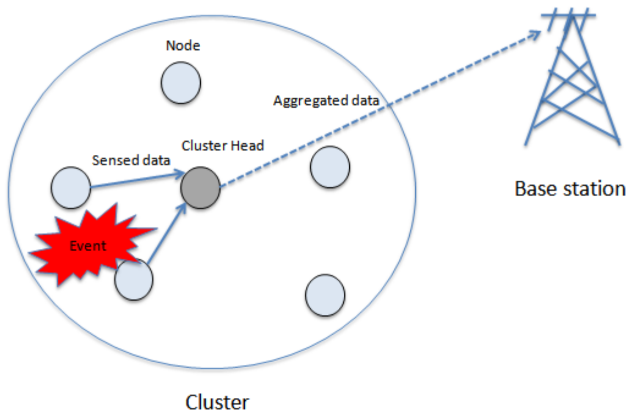

Figure 1. Event detection at the cluster head

LEACH [11,12] is one of the most popular and among the first hierarchical routing algorithms for sensor networks. It is a self-organizing, adaptive clustering protocol that uses randomization to distribute the energy load evenly among the sensors in the network. In LEACH, the nodes organize themselves into local clusters. Each cluster has one node acting as the local base station called cluster-head. This cluster-head is the intermediate point for its cluster to the sink. Because of cluster-heads make long-range transmission; the cluster-head role is energy high cost. In order to not drain the battery of a single node, LEACH includes randomized rotation of the high-energy cluster-head position such that it rotates among the various sensors. In addition, LEACH performs local data fusion to reduce the amount of data that being sent from the clusters to the base station, further reducing energy dissipation and enhancing system lifetime. At any given transmission round (or period of time), sensors elect themselves to be local cluster-heads with a certain probability. The decision about whether to be a cluster-head is made independently of the other nodes in the network. Hence no extra negotiation is required to determine the cluster-heads. When a node decides to be cluster-head, it broadcasts its status to the other sensors in the network. Based on the received broadcasted status signal strength, the network nodes estimate the communication energy needed to communicate with each cluster-head. And then, each sensor node determines to which cluster it wants to belong by choosing the cluster-head that requires the minimum communication energy.

Once all the nodes are organized into clusters, each cluster-head establishes a TDMA schedule for the nodes in its cluster. This scheduling allows nodes to switch off their radio interfaces at all times except during its transmit time, which allows to minimize the energy dissipated in the individual sensors. Once the cluster-head has all the data from the nodes in its cluster, the cluster-head node aggregates the data, by removing redundancy, and then transmits the compressed data to the sink.

SEP [16] is a proposed scheme for heterogeneous wireless sensor networks, which is composed of two types of nodes according to the initial energy. The advanced nodes are equipped with more energy than the normal nodes at the beginning. This technique prolongs the stability period, which is defined as the time until the first node failure. DEEC [17] is a distributed clustering scheme for heterogeneous wireless sensor networks. In DEEC the CHs are elected by a probability based on the ratio between residual energy of each node and the average energy of the network. The epochs of being cluster-heads for nodes are different according to their initial and residual energy. The nodes with high initial and residual energy will have more chances to be the cluster-heads than the nodes with low energy.

To satisfy that the gathered data at the sink were accurate, the operation of data aggregation must be done properly. The key is that the cluster members will be selected to give the best data fusion. Thus, the spatial correlation among the sensor observations can be exploited to drastically enhance the overall network performance. The spatial correlation can be expressed as follow; to achieve acceptable coverage, WSN applications require spatially dense sensor deployment. Consequently, numerous sensors collect information about the same event in the field. Due to high nodes density, sensors that are close than others collect the same data that means that the data correlation is important. This correlation increases with decreasing inter-node separation distance [19].

In [20] the authors gave a formula to calculate the distortion observed between the real collected data and the received one at the sink. This distortion depends on the reporting nodes number, the correlation between the reading of the reporting nodes, the correlation between those data and the event source.

Based on the distortion, Chen et al. [21] proposed a method to dynamically adapt the data reliability at the sink. The key idea is to enhance the data aggregation by varying the number of nodes that report data to the sink and/or the data reporting frequency to achieve the desired data reliability at the sink. Thus, the BS send to the CHs the adequate nodes number and the data reporting frequency that will be used in the intra-cluster when the CH collects data from its neighbouring nodes.

3. A Low Energy Time Based Energy-Efficient Clustering Technique for Routing in Wireless Sensor Networks

Zytoune et al. [22] have presented a clustering technique based on the network nodes residual energy to allow the network lifetime extension. Each node decides to be CH based on its residual energy and the average network nodes remaining energy. Our contribution consists in performing the network energy consumption by judiciously selecting the network clusters. The competition to become cluster-head is based on the residual energy related to the estimated network residual one. Because the CH makes a data aggregation to reduce the number of packets that would be transmitted toward the BS, an optimal choice of the CH and the cluster members is that this CH performs data compression, and the compressed data must be reliable.

High data correlation received at the CH allows it to perform high data compression without loosing in reliability. In dense network, the observed data presents a high similitude. This similitude can be measured through correlation. Some data correlation models were proposed. A model frequently encountered in practice is the Gaussian random field [23,24]. This model has the nice property that the dependence in data at different nodes is fully expressed by the covariance matrix. Thus, we assume in this work a jointly Gaussian model for the spatial data X measured at nodes, with an N-dimensional multivariate normal distribution GN (μ, K) (eq.1):

$$f(X)=\frac{1}{\sqrt{2\pi}.\det(K)}e^{-\frac{1}{2}(X-\mu)^T K^{-1}(X-\mu)} \tag{1}$$

Where K is the covariance matrix (positive definite), and μ is the mean vector. The diagonal elements of K are the variances $K_{ij}=\sigma_i^2$. The rest of K_{ij} depend on the distance between the corresponding nodes. Then, for any index combination I= $\{i_1, \dots, i_k\}\in\{1, \dots, N\}$, $k\leq N$, W = $(X_{i1}, \dots, X_{ik})$ is k-dimensional normal distributed. Its covariance matrix is the submatrix K[I] selected from K, with rows and columns corresponding to $\{i_1, \dots, i_k\}$. Since we assume that data at all nodes is quantized with the same quantization step, and differential entropy differs from entropy by a constant for uniformly quantized variables, we use differential entropy instead of entropy. The entropy of a k-dimensional multivariate normal distribution Gk(μ, K) is:

$$h(G_k(\mu,K))=\frac{1}{2}\log(2\pi.e)^k.\det(K) \tag{2}$$

As for two correlated random data source Xi and Xj, let H(Xi) and H(Xj) be the entropies of Xi and Xj . Then Xi and Xj can code their data using H(Xi) and H(Xj) as their coding rate. If they can communicate with each other, they can jointly code their data using a coding rate H(Xi, Xj). In [28], it has been proved that even Xi and Xj cannot communicate with each other, they can still jointly code their data using a coding rate H(Xi, Xj). The prerequisite is their coding rates are equal to their conditional entropies H(Xi|Xj) and H(Xj|Xi).

Above conclusion can be extended to multidimensional conditions. As for a data source set X = (X0, X1, X2,..., Xn), if the sources know the correlation structure, then the sources can use a joint coding rate H(X0, X1, X2,..., Xn) to code their data even they do not communicate with each other. Assume the sources in set X are arranged according to their distances to X0, then the coding rates are assigned as follows [23] (eq. 3):

$$\begin{cases} R_0^* = H(X_0); \\ R_1^* = H(X_1(X_0); \\ \dots \\ R_n^* = H(X_n(X_{n-1},\dots,X_1,X_0) \end{cases} \tag{3}$$

For a cluster, let X0 be the cluster head and (X0, X1, X2,..., Xn) are the members that are listed according to their distances to X0. The coding rates can be assigned according to equation.

The correlation function is assumed to be non-negative and decreases monotonically with the distance. We use the power exponential model since the physical event information is modelled to have an exponential autocorrelation function [24]. In this work we use the model given in (eq. 4):

$$\rho_{ij}=\sigma_S^2.e^{-\alpha.d_{ij}^2} \tag{4}$$

Many literature works that discusses the data aggregation were presented. Hua and Yum [25] presented a data aggregated maximum lifetime routing scheme for wireless sensor networks. They address the problem of jointly optimizing data aggregation and routing so that the network lifetime can be maximized. The earlier cited work [20] expresses the data distortion observed at the sink. This distortion is given by equation (5):

$$D=\sigma_S^2-\frac{\sigma_S^4}{N.(\sigma_S^2+\sigma_N^2)}(2\sum_{i=1}^{N}\rho_{si}-1)+\frac{\sigma_S^6}{N^2.(\sigma_S^2+\sigma_N^2)^2}(\sum\sum\rho_{ij}) \tag{5}$$

Where σ_S^2 represents the signal variance, σ_N^2 is the noise variance, N is the number of nodes that transmit the sensed data to the sink and ρ_{ij} is the correlation coefficient between the data collected by nodes i and j.

In this work, we propose to exploit the cluster members' data to enhance the data aggregation that will be done in the CH. As presented in equations (5) the data correlation between the detection at two nodes decreases as the distance between nodes augments. Thus, it is important that the cluster radius must be fixed to hold the data correlation between the nodes members and the CH. In the following, we exploit this idea to ensure data collection accuracy by developing a new clustering scheme.

Figure 2 represents the data distortion observed at the cluster head for different nodes network densities when the cluster radius changes. The network nodes are uniformly located in the network area that is assumed to be a square area of 100m*100m, the correlation model is supposed that α=0.1, the variance σ_S^2=1 and σ_N^2=0.1. As depicted, the distortion increases when the cluster radius augments. Then to ensure a best data collection at the cluster head, the cluster radius must be under a threshold that is defined based on the accepted distortion at the sink.

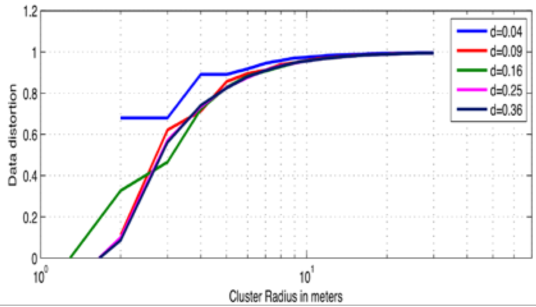

Figure 2. Data distortion vs. network nodes density

For this work we assume that all the network nodes are synchronized and immobile. To ensure nodes synchronization, some techniques suitable for WSN were proposed in the literature (e.g. [26,27]). We assume also that the cluster-head node is able to adjust its transmission radius.

Let note En(r) the residual energy of the node n at the round r, $\overline{E}(r)$ denotes the average energy of the network at round r and TCH denotes the time interval for cluster-head competition.

The proposed algorithm is a self-organizing, dynamic clustering method that divides dynamically, the network on a number of a priori fixed clusters based on the acceptable data distortion at the CH and then the sink.

In this work, we use two-level heterogeneous networks, in which there are two types of sensor nodes; the advanced nodes and normal nodes. Lets note E_0 the initial energy of the normal nodes, and f the fraction of the advanced nodes, which own a times more energy than the normal ones. Thus there are fN advanced nodes equipped with initial energy of (1 + a) E_0, and (1- f) N normal nodes equipped with initial energy of E_0. We can compute the total initial energy of the networks which is given by:

$$E_{total} = N(1-f)E_0 + Nf(1+a)E_0 \tag{6}$$

The node n becomes cluster-head for tn rounds. In homogenous networks, to guarantee that there are average p_{opt}N cluster-heads every round, LEACH let each node n becomes a cluster-head once every tn =1/p_{opt} rounds. The network nodes will have different residual energy when the network evolves. If the rotating epoch tn is the same for all the nodes as proposed in LEACH, the energy will be not well distributed and the low-energy nodes will die more quickly than the high-energy nodes. DEEC protocol, choose different tn based on the residual energy En(r) of node n at round r.

The real value of the average energy of the network at the round r is given by (7):

$$\overline{E}(r) = \tfrac{1}{N}\sum_{n=1}^{N} E_n(r) \tag{7}$$

To compute $\overline{E}$ (r) by Equation (7), each node should have the knowledge of the total energy of all nodes in the network every round. It is obvious that exchanging messages to compute this value is energy expensive. So we process with an estimation of this value

An estimation of this parameter is given by Equation (8):

$$\overline{E}(r) = \frac{E_{total}}{N}\left(1-\frac{r}{R}\right) \tag{8}$$

If we note the total energy dissipated in the network during a round by Eround, then:

$$R = \frac{E_{total}}{E_{round}} \tag{9}$$

$$E_{round} = L(2NE_{elec} + NE_{DA} + k\varepsilon_{mp}d_{toBS}^4 + N\varepsilon_{fs}d_{toCH}^2) \tag{10}$$

k is the number of clusters, E_{DA} is the data aggregation cost which is expended in the cluster-heads, d_{toBS} is the average distance between the cluster-head and the base station, and d_{toCH} is the average distance between the cluster members and the cluster-head. If the nodes are uniformly distributed in a square M*M area, from [5,29] we can give (11):

$$d_{toCH} = \frac{M}{\sqrt{2k\pi}} \quad and \quad d_{toBS} = 0.765.\frac{M}{2} \tag{11}$$

Our goal is to form clusters with the same area. So, each cluster has a radius RCH. This radius is determined by the total distortion accepted in the CH.

And then, the number of clusters is calculated by the following equation (12):

$$k = \frac{M*M}{\pi.R_{CH}^2} \tag{12}$$

The operation of the proposed protocol is broken up into rounds where each round consists of a set-up phase and steady-state phase. In the following sub-sections we will detail each of these phases.

Set-up phase

In the beginning of each epoch, each node n uses the equation (13):

$$t_i = \frac{E_i}{\overline{E}(r)}T_{CH} \tag{13}$$

To calculate the instant when the node broadcasts its candidacy for cluster-head role on a radius RCH. Each node in this radius receives this message and belongs to this cluster. Thus, the cluster-heads are uniformly distributed on the network area. Once the nodes decide to which cluster belong, they inform the cluster-head transmitting a join-request message to it, using CSMA/CA MAC protocol. A header, the node ID and the cluster-head

ID, forms this message that is a short one. This message size grants to reduce the time channel access and the transmission energy cost.

Steady-State Phase

Once the clusters are established, the nodes transmit their data messages towards the cluster-head. When the cluster-head receives all the nodes data, it performs its fusion, to form a new message that sent to the base station.

4. Simulation Results

To assess the performance of the proposed algorithm, we run some simulations using Matlab. Our proposition is compared to DEEC protocol [17]. The used parameter values in our work are given in the following Table 1.

Table 1. Simulation parameter values

Description	Symbol	Value
Network dimension	M*M	100m*100m
Network nodes number	N	100
Data packet length	L	4000bits
Control packet length	Lctr	200bits
DEEC protocol optimal probability	P_{opt}	0.1
Advanced nodes percentage	f	20
Fraction of advanced nodes energy to normal nodes	a	3

Figure 3 represents the network lifetime for the proposed protocol compared to DEEC. In this Figure we give the network lifetime until 1%, 10%, 20%, 50% and 70% of network nodes have their energy depleted. As we can see, except the first node dies, the proposed protocol (LETC) permits to extend the network lifetime for extra transmission rounds compared to DEEC. For the lifetime defined until the first node has its energy consumed, LETC outperforms DEEC for a determined Cluster Head radius.

Figure 4 gives the number of nodes still alive for every transmission rounds, the Cluster radius for LETC is at 60m. As depicted, LETC permits to extend to network time usage compared to DEEC. This extension is given in Figure 5 where the network lifetime extension percentage is presented for each node dead, which means that the proposed technique allows the network lifetime extension until the major network nodes are dead.

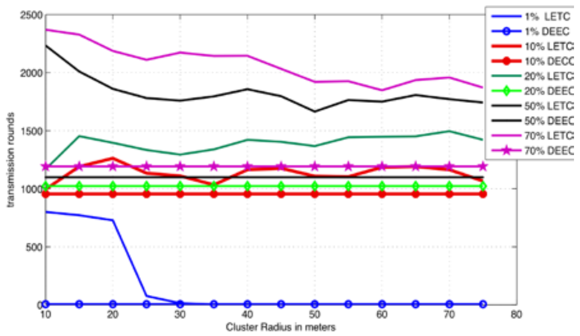

Figure 3. Network lifetime with α=0.1

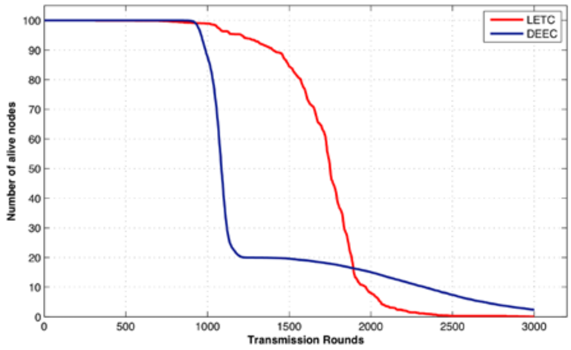

Figure 4. Network lifetime with R_{CH}=60m and alpha=0.1

As depicted in Figure 4, the proposed technique exploits the nodes energies equitably since the network nodes die randomly better than DEEC where the nodes with additional energy are the last dyeing nodes.

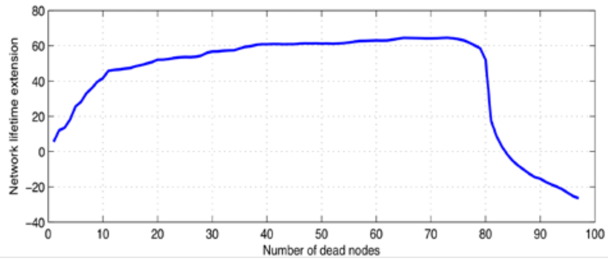

Figure 5. Relative Network lifetime extension.

5. Conclusions

In this paper, we have proposed a distributed clustering based routing protocol for WSNs. We have interested in performing the cluster-heads distribution over the network area. So, the network is equitably partitioned and then the sink-collected data are more accurate. Through the simulation, we demonstrate that the proposed algorithm allows a network lifetime extension compared to the most known clustering algorithms in this area. As future work, we will reconsider the dynamic selection of cluster surface based on the observed distortion at the cluster head.

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