Evolutionary Based Clustering Protocol for Wireless Sensor Networks

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Abstract. Many cluster based routing protocols have been developed in order to enhance the network lifetime, but the potency of clustering in energy management highly relies on the optimality of clusters. Optimal cluster formation is the chief source of challenges in clustering protocols. In this paper, new approach has been introduced to formulate the optimization problem in the partition of networks into optimal organization of clusters. The optimization problem consists of finding optimal configuration of clusters such that the distance of cluster heads from the pre-computed cluster centers, communication cost of nodes to transport data and the expected energy dissipation of the network per the residual energy of cluster heads are minimized. The solution to the devised nonlinear clustering problem is found using the genetic algorithm. The genetic algorithm toolbox is developed in C++ and integrated with OMNeT++ simulation platform to implement the protocol. The experimental results verify that the proposed protocol extends the network lifetime compared to the prominent LEACH, LEACH-C and CHEF protocols.

Keywords: Clustering protocol · Wireless sensor networks · Routing protocol

1 Introduction

Wireless sensor networks (WSNs) are primarily designed to furnish the user with the required information in an interest zone ranging from less infrastructure region to physically challenging environment. The integrations of different disciplines such as microelectronics, wireless communication, signal processing and network protocols make the realization of these micro-sensor devices. The architecture of sensor node typically consists of sensing, processing, communication and power supply modules. As the military forces evolved from mechanization to information, sensor networks supply the necessary information for commander of an army to have military dominance through detection of biological, nuclear and chemical attacks in the battlefield. Target tracking and conflict zone inspection are also the potential applications of sensor

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networks in military surveillance [1, 2]. Medical doctors can easily give persistent treatment and follow up the physiological status of their patients at far distance if the customers are equipped with wireless medical sensors [3]. Nuclear emission detection in nuclear power plant, active volcano recognition and forest fire detection are some of the applications of sensor networks in environmental monitoring and control [4]. Nowadays, even buildings are equipped with wireless sensors to reduce the energy wastage by regulating the air conditioning, temperature, ventilation, and humidity of rooms [5].

Wireless sensor networks are somehow similar to other distributed systems. But, it has its own unique challenges and constraints which initiate the system designers to develop new hardware architectures, network protocols and algorithms that are well suited for WSN applications [6–8]. Considering that nodes are left unattended after deployment, they are exposed to malicious attack and intrusions [9, 10]. Generally, self-adaptation, healing, protection and organization are the main challenges in sensor network design. Clustering is one of the methods broadly used to reduce the energy consumption of network and effectively utilizing the channel bandwidth [11–13]. In clustering, leaders are selected and the rest of nodes send their data to the respective cluster leaders so as to reduce the communication distance. The data collected per cluster is highly correlated that the cluster leaders aggregate the received packets from their members before forwarding the data to the base station.

In this paper, we propose Evolutionary based Clustering Protocol, termed ECP to build efficient clusters in wireless sensor networks. The distance of cluster leaders from the pre-computed centroid of clusters, the communication cost of nodes to transport data and the expected energy of dissipation of networks per the remaining energy of cluster leaders are the optimization parameters in the formulated clustering problem. Of the parameters used in optimal configuration of clusters, the distance of candidate Cluster Heads (CHs) from the centroid of clusters can be computed by finding the center points of data points (spatial position of nodes) using the Fuzzy C-Means (FCM) clustering algorithm. The problem of finding cluster centers from the set of geographical position of nodes is formulated as nonlinear constrained optimization problem. The FCM and genetic algorithm (GA) toolboxes are developed in C++ and integrated with OMNeT++ simulation environment to implement the protocol. The experimental results prove that ECP outperforms LEACH, LEACH-C and CHEF protocols.

2 Related Work

In [14], Low Energy Adaptive Clustering Hierarchy (LEACH) protocol has been presented. The data gathering period in LEACH has cluster setup and steady state phases. In cluster setup phase, nodes are randomly configured as cluster head based on the set threshold model, $T(n)$ and their corresponding cluster members will be recognized. Nodes randomly choose any number between 0 and 1 among which those that are able to take a number less than the value of $T(n)$ is selected as cluster head.

$$T(n) = \begin{cases} \frac{p}{1-p\,(r \bmod \frac{1}{p})} & , \textit{if } n \varepsilon G \\ 0 & , \textit{otherwise} \end{cases} \quad (1)$$

The symbols p, r and G respectively define the desired percentage of cluster leaders, current round number and the set of nodes which are not designated as cluster leader in previous $1/p$ rounds. The cluster heads announce their presence using Carrier Sense Multiple Access (CSMA) Medium Access Control (MAC) protocol so as to identify the cluster members. Then, the cluster heads assign Time Division Multiple Access (TDMA) slots to their children. During steady state phase, the cluster heads receive data from their members, aggregate correlated data and forward it to the base station by making the use of spreading codes and CSMA MAC protocol. The random configuration of clusters in LEACH not only affects the number but also distribution of cluster heads. Regardless of their energy, all nodes are equally probable to act as cluster leader in LEACH that will most likely reduce the lifetime of lower energy nodes in the course of protocol operation. Unlike the distributed cluster formation in LEACH, the paper in [15] describes centralized version of LEACH (LEACH-C) protocol that will initially build clusters at the base station and then announce the details of network back to nodes. LEACH-C protocol configures the clusters such that the communication distance within the cluster is minimized. The protocol applies Simulated Annealing (SA) algorithm to minimize the sum of the square of Euclidean distance between regular nodes and cluster leaders.

The authors in [16] present Fuzzy logic based Cluster Head Election system, termed CHEF. The residual energy and the sum of Euclidean distance of a node from its neighbors are the input variables of the fuzzy system. Each node randomly takes any number between 0 and 1 to construct clusters and asserts itself as a candidate cluster head whenever the generated number is less than the pre-set threshold value.

The authors in [17] present instantaneous clustering protocol for WSNs. The authors design a clustering scheme that is not only able to minimize the time required to setup the clusters but also increase the energy efficiency networks. Instead of using vote in clustering, the authors use the pre-assigned chance of being cluster head so as to accelerate the selection process. The regular nodes in existing methods use acknowledgments (ACKs) to verify the reception of ID of the cluster head. However, concurrent ACKs from multiple nodes within the cluster lead to signal collision. For that reason, the authors avoid ACKs mechanism in clustering. Instead, only the cluster heads are allowed to contend and broadcast their presence during the given period. In order to assure the delivery of ID of the cluster head without collision, the authors formulate the optimal number of time slots adequate for each cluster head.

3 Modelling Energy Consumption of Wireless Sensor Node

The simplified model has been used for radio hardware energy dissipation. The free space and multipath channel models [18] have been used for the experiments in this paper. The power amplifier is adjusted such that the desired output power is delivered to antenna interface to compensate for the path loss during electromagnetic radiation.

Let the energy consumed in the transceiver to receive and transmit data over a distance d be ERx and ETx respectively. Then, the energy consumption in the radio hardware to transmit or receive l bits of data can be computed via the following equations.

$$ETx = \begin{cases} l * Eelc + l * efs * d^2, & d < do \\ l * Eelc + l * emp * d^4, & d \geq do \end{cases} \tag{2}$$

$$ERx = l * Eelc \tag{3}$$

$$do = \sqrt{\frac{efs}{emp}} \tag{4}$$

The constant $Eelc$ refers to per-bit energy consumption of the transmitter or receiver electronics. The coefficients efs and emp are energy dissipation factors in the power amplifier for free space and multipath channel models respectively.

4 Proposed Protocol Design

4.1 Problem Formulation

Consider a WSN with the set of nodes that are randomly placed within the domain of an interest region. At the beginning of every cluster setup phase, nodes send their energy and geographical position parameters to the base station so as to trigger clustering of nodes. Given a network of sensors with known clustering parameters, the problem consists of finding the set of nodes that can be configured as cluster heads to minimize the overall data transmission cost in the network. The base station considers the spatial position of node as a data point to make up dataset pool based on which the pending cluster analysis starts. Data points in the dataset pool will be grouped into clusters such that the similarity of data points measured in terms of Euclidean distance is strong within the cluster. Each cluster is known for its cluster center (centroid) from which the sum of squared distance of data points within cluster is minimized. The analogy is that nodes very near to the cluster centers should be elected with high probability as the potential cluster leaders in order to minimize intra-cluster communication cost provide that they have sufficient amount of residual energy. Given N number of nodes in WSN area, let the desired number of clusters is k. Consider the data point matrix $\mathbf{Z}$ that consists of vectors $\mathbf{z}i, i = 1, \ldots, N$ in its column where the vectors are actually (x, y) coordinates of nodes. Similarly, let the vector of cluster centers is represented as follows.

$$\mathbf{C} = [\mathbf{c}1\ ,\ \mathbf{c}2\ ,\ \ldots,\ \mathbf{c}k] \tag{5}$$

The fuzzy clustering has been used for assignment of data points into clusters. Unlike the traditional or hard clustering techniques for which the data point totally belongs to one of the clusters, the fuzzy clustering enables natural grouping of data where the given data point belongs to many clusters with different membership degrees. Let the degree of membership of node i to cluster j is represented as uij and m is the fuzzy control parameter. The optimization problem is to find the feasible set of clusters so that the sum of Euclidean norm of the given data points to the cluster centers is minimized. Hence, the problem of grouping data points to clusters is based on minimization of the following objective function.

$$Jc = \sum_{i=1}^{N} \sum_{j=1}^{k} (uij)^{m} \|\mathbf{z}i - \mathbf{c}j\|^2 \quad 1 \le m < \infty \tag{6}$$

$$s.t \begin{cases} uij \in [0,1], & 1 \le i \le N\ ,\ 1 \le j \le k \\ \sum_{j=1}^{k} uij = 1\ , & i = 1,\, 2, \cdots, N \\ 0 < \sum_{i=1}^{N} uij < N, \quad 1 \le j \le k \end{cases}$$

The minimization of the above objective function is nonlinear constrained optimization problem that can be solved by a range of methods among which the fuzzy c-means clustering algorithm has been used. The fuzzy c-means clustering algorithm finds the solution through iteratively updating the membership degrees and cluster centers as follows until the algorithm converges.

$$uij = \frac{1}{\sum_{l=1}^{k} \left(\frac{\|\mathbf{z}i - \mathbf{c}j\|}{\|\mathbf{z}i - \mathbf{c}l\|} \right)^{\frac{2}{m-1}}}, \quad 1 \le i \le N\ ,\ 1 \le j \le k \tag{7}$$

$$\mathbf{c}j = \frac{\sum_{i=1}^{N} (uij)^{m}\, \mathbf{z}i}{\sum_{i=1}^{N} (uij)^{m}}, \quad 1 \le j \le k \tag{8}$$

Let $\mathbf{U}f$ defines the fuzzy partition matrix that consists of *vectors of* membership degree of nodes to the given clusters and represented by $N\ x\ k$ matrix as follows.

$$\mathbf{U}f = \begin{bmatrix} u11 & u12 & \cdots & u1k \\ u21 & u22 & \cdots & u2k \\ \vdots & \vdots & \vdots & \vdots \\ uN1 & uN2 & \cdots & uNk \end{bmatrix} \tag{9}$$

The pseudocode of the fuzzy c-means clustering algorithm is shown in Algorithm 1. The algorithm iteratively computes the fuzzy partition matrix and the termination criteria is when the difference between current and previously computed partition matrix resides below the predefined threshold value ε, as shown in the following equation.

$$\left\| \mathbf{U}f^{now} - \mathbf{U}f^{previous} \right\| < \varepsilon \tag{10}$$

Algorithm 1: Fuzzy C-Means (FCM)

Input: spatial position of nodes
Output: vector of cluster centers
begin
  initialize $\mathbf{U}f$
  repeat
    for cluster $j = 1$ to k **do**
      $\mathbf{c}j \leftarrow$ compute the cluster center
    end for
    update $\mathbf{U}f$
  until the algorithm converges
  return $\{\mathbf{C}\}$
end

When the fuzzy c-means clustering algorithm converges, the set of cluster centers for the given coordinates of nodes in WSN field will be identified and then it can be used as one of the input parameters in genetic algorithm based computation. Let the set of cluster heads and regular nodes are stored in the variables H and R respectively such that $H \cup R = N$. Let dij represents the distance between node i and j. Suppose $CTij$ defines the cost of transferring data from node i to j and ϕj is the amount of data node j must send. In addition to minimizing the communication cost, the remaining energy of cluster leaders per expected dissipation of energy should be increased in order to extend the network lifetime. Suppose the residual energy of node i is represented as ei. Hence, the problem of optimal network clustering is a combinatorial optimization problem that consists of finding the possible combination of cluster heads so that the following objective function is minimized

$$fobj = \begin{cases} \sum\limits_{i \in N} si * dij,\ j = \arg\ \min_h\{\, dih,\ h\ \in\ \mathbf{C}\} + \sum\limits_{i \in H} \left(\sum\limits_{j \in R} qij\, CTji + CTibs \right) + \\ \dfrac{\sum\limits_{i \in H} \left(\left(\sum\limits_{j \in R} qij\ \phi j\, Eelc \right) + \phi\, i\, Eelc + \varepsilon a\, dibs^m \right)}{\sum\limits_{i \in H} ei} \end{cases} \tag{11}$$

The symbol εa in the above equation refers the amplifier coefficient and the constant m defines the path loss exponent. Consider the parameter Tx^j that defines the transmission range of node j. The symbols si and qij are the decision variables and can be represented as follows.

$$si = \begin{cases} 1 & \text{if node } i \text{ configured as } CH \\ 0 & \text{otherwise} \end{cases}$$

$$qij = \begin{cases} 1 & \text{if } \|dij\| \leq Tx^{j} \\ 0 & \text{otherwise} \end{cases}$$

4.2 Solution Finding Based on Genetic Algorithm

The genetic algorithm starts with initial population $(Pt \,|\, t = 0)$ of chromosomes which are generated randomly as preliminary solutions to the problem but through iterative randomization and guided search mechanisms, the solutions are transformed to finer results. The best chromosome (*Cbest*) in history of population generations is the basis for cluster configuration. The WSN nodes are represented by sequence of bits in binary encoded chromosome structure. Hence, the size (length) of a chromosome is equivalent to the dimension of network which is prescribed as the number of nodes in WSN area. The content of a chromosome is uniquely identified by *gene index* and *gene value* pair in which the *gene value* and *gene index* are the state of node to act as cluster leader and ID of node respectively. Consider the *gene value* of a chromosome at *gene index* i is represented as $g(i)\ \forall\, i \in \{1, 2, \ldots, N\}$. Then, it can be mathematically expressed as follows.

$$g(i) = \begin{cases} 1 & \text{if node } i \text{ configured as cluster leader} \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

Suppose r defines the size of population which is fixed to the same value over generations and let *len* symbolizes the length of a chromosome, then the chromosomes of population in each generation can be designated as follows.

$$Cr^{g} = \left\{ Cr\overset{g}{j} \;\middle|\; 1 \leq j \leq r\,,\ \ Cr\overset{g}{j} = (\, g(1)\,, g(2)\,, \ldots, g(i)\,, \ldots, g(n)\,)\,,\ n \leftarrow len \right\} \tag{13}$$

The initial population of chromosomes are evolved to future generations through the genetic recombination and mutation of those individuals which are allowed to breed based on the given selection strategy. In our algorithm, chromosomes are selected for mating based on Roulette-Wheel selection scheme where the selection probability of an individual increases with the rank (fitness value) of a chromosome. A single point *crossover* is applied to chromosomes in the mating pool in which a point (crossover site) is selected at random over the span of chromosome and the *gene value* of parts of parent chromosomes are exchanged to produce a pair of child chromosomes. In order to alleviate the premature convergence for which the solution tends to stick into local optimum, the *mutation* operator is applied to child chromosomes. The fact that *mutation* adds variation to generation allows the algorithm to go through a wide range of search space in an attempt to achieve the global optimum. Since *mutation* is a divergence operation, it should happen less frequently than the *crossover* operation in order to speed up the convergence rate. The pseudocode of genetic algorithm is shown in Algorithm 2. In the late stages of data gathering periods, some nodes may run out of energy for which the base station must update the history of those nodes in the chromosome structure. Hence, at end of population *initialization*, *crossover* and *mutation* operations, the *gene value* of such nodes should be updated using *chromosome repair* operation to avoid them from possible inclusion in the cluster leaders list. The evolution operators are applied repeatedly till the algorithm is terminated in the late evolving periods at which the solutions are no longer changed.

Algorithm 2: Genetic Algorithm

```
begin
    t ← 0 {generation counter}
    Pt ← generate initial population
    while t < max generation count do
        Ft ← evaluate (Pt)
        C_best ← update_best (Pt, Ft)
        Pt' ← genetic_operation (Pt)
        Pt'' ← chromosome_repair (Pt')
        Pt ← Pt''
        t ← t + 1
    end while
end
```

4.3 Network Configuration

Due to the stochastic nature of genetic algorithm, there is an appearance of spike in the number of clusters. Hence, upon the convergence of the GA computation, the cluster maintenance module takes the GA suggested clusters and find out those that will create fair distribution of clusters in WSN field. Normally, good distribution of clusters can be obtained if the cluster leaders are at significant distance to each other so that the average of regular nodes can easily reside within the minimum transmission diameter of cluster leaders. As it is stated in the previous section, the desired number of clusters is k. The cluster maintenance module takes k cluster leaders randomly from the pool of GA suggested clusters. Then, it will find out those that are able to maximize the spatial distance between cluster leaders so as to preserve good distribution of clusters in WSN region. Hence, the problem of finding k cluster leaders from the GA suggested clusters is based on maximization of the following objective function.

$$fobj = \sum_{i \in \mathbf{CL}} \left(\sum_{j \in \mathbf{CL}, j \neq i} \| dij \| \right) \tag{14}$$

The parameter d_{ij} represents the distance between cluster leaders i and j. The GA suggested cluster leaders are stored in vector **CL**. Once the clusters are configured, the base station announces the details of network configuration back to nodes. The configuration consists of selected cluster heads and the time schedule (TDMA slot) of regular nodes. The nature of steady state data transmission phase is much similar to LEACH protocol and for this reason the detail is omitted here.

5 Performance Evaluation

5.1 Simulation Environment

The experiment is done using Objective Modular Network Test-bed (OMNeT++) simulation platform. The networks of 100 sensor nodes are uniformly deployed across $100\,\text{m} \times 100\,\text{m}$ WSN area. The configuration parameters used in the simulation are initial energy = 2 J, base station location = (175, 50) m, control packet size = 25 bytes, data packet size = 500 bytes, *Eelc* = 50 nJ/bit, energy consumed for data aggregation (*Eda*) = 5 nJ/bit/signal, *efs* = 10 pJ/bit/m2, *emp* = 0.0013 pJ/bit/m4 and TDMA frames per round = 6. The GA parameters used in the experiment are population size = 50, mutation rate = 0.001, crossover rate = 0.8 and generations count = 2000.

5.2 Experimental Results and Analysis

The base station iteratively executes the genetic algorithm till the convergence criterion is achieved. The plot in Fig. 1 depicts the minimum and maximum fitness of chromosome per each generation and the highest fitness recorded in the history of generations for randomly taken data gathering round. Initially, the fitness tends to get better quickly and as the iteration proceeds to the convergence point, the algorithm hardly shows improvement in the value of fitness. The simulation result shows that the algorithm converges after 1000 generations are gone for the selected data gathering round.

Owing to the presence of duplicate data in network, the death of a few nodes does not severely affect the quality of network except being a good indication of the kick-off of quality degradation. From this perspective, the time elapsed till 50% of nodes die (HND) is thus an acceptable metric to numerically measure the network lifetime compared to other metrics, viz. the time at which the first node runs out of energy (FND) and the time at which the last node dies (LND). For most application of WSNs, the network is considered non-functional right after HND. Figure 2 describes the number of functional nodes versus time. The simulation result shows ECP improves the network lifetime by 42.96%, 7.71% and 5.01% compared to LEACH, LEACH-C and CHEF protocols respectively. The substantial rate of premature death of nodes in LEACH is due to random configuration of clusters in which incapable nodes (nodes having lower energy) are not blocked to act as cluster head. The delayed death of nodes in ECP is the manifestation of fair distribution of load among sensors. Nodes drain energy nearly at the same rate in ECP than its counterparts. Owing to this fact, higher death rate and steeper gradient appear following the death of the first node in ECP than

LEACH, LEACH-C and CHEF protocols. ECP also dominates LEACH, LEACH-C and CHEF protocols in terms of FND, HND and LND metrics. After the death of first node, the network is mostly considered unstable even if the quality is not quickly diminished at high rate. Hence, the proposed protocol has higher network stability than LEACH, LEACH-C and CHEF protocols.

One of the root causes of premature death of nodes in WSN region is unbalanced load distribution in the network. Unbalanced load hastens the power consumption rate of the particular set of nodes. Due to aforementioned problem, the variance of energy expenditure among nodes shall be reduced to extend the system lifetime. The standard deviation of the residual energy of nodes in each simulation round is depicted in Fig. 3. The simulation result shows that ECP improves the degree of energy equilibrium among nodes compared to LEACH, LEACH-C and CHEF protocols. LEACH-C dominates LEACH and CHEF protocols in terms of load balance since the clusters are configured at the base station. In addition to load balance, the overall energy consumption of nodes per each round must be reduced to maximize the residual energy of the network. Figure 4 shows the network energy consumption in each round for the four protocols. The result proves ECP has reduced energy usage than LEACH, LEACH-C and CHEF protocols. The average energy consumption of nodes is also examined for randomly taken simulation rounds.

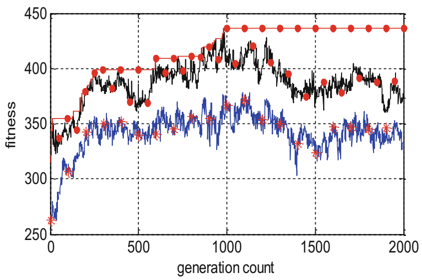

Fig. 1. Fitness of chromosome per each generation

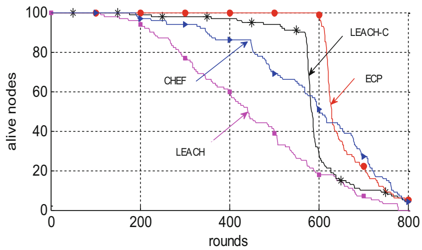

Fig. 2. Number of functional nodes versus time

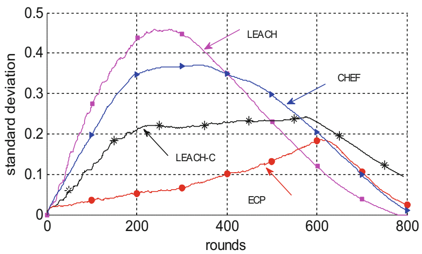

Fig. 3. Standard deviation of residual energy of nodes

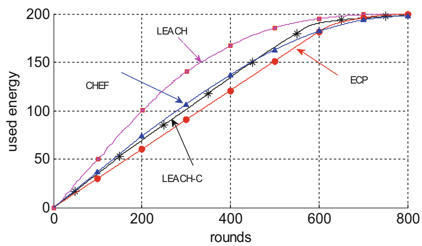

Fig. 4. Consumed energy of network over time

6 Conclusion

Wireless sensor networks are typically characterized by inherent shortage of energy. Unlike the traditional computer networks, energy conservation is the prominent and critical issue in design of sensor networks in which other parameters such as delay, reliability and throughput are treated as secondary requirements. Effective use of channel bandwidth, data aggregation and reduced consumption of energy are the typical benefits of cluster based protocols. In this paper, we present optimization of cluster formation based on the computational models of evolutionary algorithm. Considering that the exhaustive search methods do not find optimal solutions to NP-Hard problems within polynomial bounded time, the genetic algorithm has been applied to find optimal or suboptimal solution at reduced computational time. In cluster setup phase, the base station configures the cluster heads and nodes are then informed about the details of configuration to begin data dissemination. The simulation results prove that the proposed protocol dominates LEACH, LEACH-C and CHEF protocols.

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