Energy-Efficient Clustering Based on Game Theory for Wireless Sensor Networks

Shelly Salim and Sangman Moh
Dept. of Computer Eng., Chosun University
Gwangju, South Korea
shellysalim22@gmail.com, smmoh@chosun.ac.kr

Abstract
Clustering in wireless sensor networks has to consider energy conservation due to the limited energy resources of sensor nodes. In this paper, a cost- and reward-based (CORE) clustering algorithm using game theory is proposed, which aims to save energy and prolong network lifetime. The probability that a sensor node declares itself a cluster head is formulated by considering both the cost and the reward. Furthermore, the reward has a significant effect on cluster heads by allowing them to be idle for certain durations. The simulation results show that CORE clustering significantly outperforms conventional clustering methods in terms of network lifetime and the amount of data sent to the sink.

Keywords: Wireless sensor network, clustering, cluster head selection, game theory, energy efficiency, performance.

1. Introduction

Wireless sensor networks (WSNs) are collections of small and autonomous sensor nodes with a limited energy source. The nodes sense their environment, collect specific data requested or needed by users or applications, and send them to an entity called the sink. WSNs are one type of application-driven wireless ad hoc network [1]. They are developed to monitor and control events, so the sensor nodes are scattered within the monitored area. Because of the advancements in wireless technologies and electronics, the sensor nodes are relatively low-cost and of small size [2]. In general, numerous sensor nodes are randomly deployed over the target area. The data collected by the sensor nodes could be sent to the sink in a single-hop or multi-hop manner. Some applications and ongoing projects for WSNs are in habitat monitoring, health monitoring, battlefield surveillance, intrusion detection, inventory management, etc.

Due to the small size and wireless nature of sensor nodes, they are battery-powered. Sometimes the monitored areas are remote or inaccessible, so it is impractical to recharge or change the batteries of those sensor nodes. As a result, network lifetime largely depends on battery capacity of the sensor nodes. Moreover, since the sensor nodes are relatively cheap, they might even be disposable. Therefore, they are expected to operate as long as possible before energy depletion and without reinstallation. Accordingly, energy conservation for sensor nodes is one of the main issues in WSNs. Energy conservation strategies can be included at the node level, medium access control (MAC) level, and network level [3]. Dynamic voltage scheduling and dynamic power management are examples of energy conservation efforts at the node level, whereas transmission power adjustment is an example at the MAC level. Studies on network-level energy conservation tend to look for energy-efficient and robust methods of route setup and data transmission or relay. In this paper, the authors focus on network-level energy conservation.

Typically, sensor nodes operate unattended, and thus, they should have a self-organizing ability. They might determine amongst themselves how to cooperate in order to extend network lifetime. As an attempt at network-level energy conservation, the sensor nodes might perform hierarchical or cluster-based routing. A number of sensor nodes are grouped together to form a cluster, which has a cluster head. The sensor nodes belonging to a particular cluster do not send their collected data directly to the sink. Instead, they send the data to their cluster head. The cluster heads are responsible for forwarding the data to the sink, either directly or by relaying it through other cluster heads. Clustered sensor networks can significantly reduce energy consumption as well as network congestion and data collisions, compared to non-clustered networks. Figure 1 shows a clustered wireless sensor networks.
In a non-clustered network, all sensor nodes send their data directly to the sink. This method requires a long transmission range for all sensor nodes. Hence, it consumes higher energy and increases the probability of network congestion and data collisions because all the traffic is destined for the same node (i.e., the sink). In a clustered network, however, the sensor nodes have to send their data to their cluster heads. Then the cluster heads forward the data to the sink. This method reduces traffic to the sink, and thus lowers network congestion and data collisions. Similarly, the number of retransmissions also becomes smaller, resulting in energy savings. Clustering could also reduce the transmission range needed by the sensor nodes. Furthermore, adjacent sensor nodes might report similar data [4]. Instead of sending all individual data directly to the sink, by clustering, the cluster head might perform data aggregation, thus reducing the volume of data significantly.

Game theory is a decision-making theory in uncertain and interdependent situations [5]. It outperforms mathematical analysis of wireless ad hoc networks due to characteristics such as complex mobility and traffic models, dynamic topology, and unpredictable link quality [6]. In this paper, a clustering method using game theory that considers the cost and the rewards of a node becoming a cluster head is proposed, which is called cost- and reward-based (CORE) clustering. It aims to save energy and prolong network lifetime. Besides energy conservation, the sensor nodes must also deliver their data to the sink. It is undesirable for a sensor network to consume very little energy but to not send enough data to the sink. Similarly, a sensor network that sends a lot of data to the sink while consuming a high amount of energy is also undesirable. According to our performance study, the proposed CORE clustering significantly outperforms conventional clustering methods in terms of network lifetime and the amount of data sent to the sink.

The rest of this paper is organized as follows: The following section introduces game theory and its application in WSNs. Section 3 presents the proposed CORE algorithm on the basis of game theory. In Section 4, the performance of CORE clustering is evaluated and compared to the two existing algorithms of probability-based clustering and clustered routing of selfish sensors (CROSS). Finally, Section 5 covers the conclusions from this paper.

2. Preliminaries

Game theory is decision-making under uncertain and interdependent situations; that is, the actions of the decision makers affect other decision makers. It models and analyzes interactive decision conditions to predict the result of interactions among decision makers. There are broad applications of game theory for WSNs. An extensive survey was carried out [7] and one of the findings was that typical game theories applied in WSNs include coalitional game theory and evolutionary game theory. Coalitional, or cooperative, game theory performs grouping and selects strategies to maximize the utility of the groups; evolutionary game theory analyzes the effect of dynamic strategy adjustments. Another finding is that the major roles of game theory in WSNs are power control, packet forwarding, topology control, target
tracking, and routing protocol design. In routing protocol design, some clustering algorithms based on game theory are also proposed.

A clustering mechanism called clustered routing of selfish sensors (CROSS) was proposed in [8]. It is based on a clustering game to select a number of nodes as cluster heads. The clustering game showed that, when there are a large number of sensor nodes, the probability that any one node will declare itself a cluster head is reduced. In addition, it reaches equilibrium when only a single node in the entire network declares itself a cluster head. In other words, equilibrium is when there is one cluster in the whole network. However, when there is only one cluster in the whole network, the benefits of having a clustered network is not obtained. Moreover, CROSS did not include an energy conservation plan.

In this paper, the authors adopt the basic game-theoretic analysis of CROSS [8] and add (i) a combination of the cost of being a cluster head and residual energy, and (ii) the reward for being a cluster head. Our proposed method is called cost- and reward-based (CORE) clustering, which will be presented and evaluated in Sections 3 and 4, respectively.

3. Proposed Clustering Scheme

In this paper, the authors adopt the clustering game in CROSS, that is, the game played by the sensor nodes in order to select cluster heads. In CORE clustering, the authors add a reward to the clustering game. The clustering game (CG) is defined as \( CG = < N, S, U > \), where \( N \) is the set of players (sensor nodes), \( S \) is the set of strategies, and \( U \) is the set of payoffs or utility functions that each player wants to maximize. There are two strategies in this game, and each player has to choose one of the strategies. The strategies are whether to be a cluster head (CH) or to be a cluster member (CM), that is \( S = \{ \text{CH}, \text{CM} \} \). Each strategy taken by the players has a payoff as presented in Table 1.

| Table 1. The payoffs for two-player clustering game. |
|-----------------|-------------------|-------------------|
| CH              | CM                |
| \((v + c + r), (v + c + r)\) | \((v + c + r), v\) |
| \(v, (v + c + r)\) | 0, 0              |

If a node decides to be a CM and other nodes also choose to be a CM, then they get zero payoff because they cannot relay their data (no cluster head exists because no node becomes a CH. If a node decides to be a CH and other nodes choose to be a CM, then the CM nodes could send their data to the sink via the CH. The nodes that play a CM get a payoff, \( v \), and the nodes that play a CH get a payoff \((v + c + r)\), where \( c \) is the cost of being a cluster head and \( r \) is the reward. The CH nodes suffer from the cost because cluster heads consume more energy for data reception, data aggregation and forwarding to the sink the data that come from the member sensor nodes. However, to encourage nodes to become cluster heads so the data from the cluster members can be relayed, a reward is given to the CH nodes.

In game theory, there is a concept of the Nash equilibrium. The Nash equilibrium is a strategy tuple that leads to a mutual best response, or maximum utility. Let us find the Nash equilibrium of this clustering game. The assumption is that the reward is lower than the cost, and the cost is lower than the payoff of being able to transmit data: \( r < c < v \), and \((v + c + r) < v\). If some players chose to be a CH, then the other players get payoff \((v + c + r)\) for being a CH and payoff \(v\) for being a CM. Since \( v > (v + c + r)\), then the other players would want to be a CM. If some players chose to be a CM, then the other players would get payoff \((v + c + r)\) for being a CH and payoff 0 for being a CM. Since \((v + c + r) > 0\), the other players would want to be a CH. Therefore, the two strategy tuples (CH, CM) and (CM, CH) are the Nash equilibria. Let’s assume that the reward is higher than the cost, then \( c < r < v \) and \((v + c + r) > v\). In this case, there is one dominant strategy [9], which is to play a CH. Since it is undesirable that every node to be a CH, the authors hold to the assumption that the reward is smaller than the cost: \( r < c \).

Next, the authors extend this to a mixed strategy where the players randomize their strategies based on probability. The authors assume that the probability of a player being a CH is \( p \) and that of being a CM is \((1 - p)\). The payoff when playing a CH is independent of the other players’ strategies; that is, \( U_{CH} = (v + c + r) \). The payoff when playing a CM is dependent on other players’ strategies, and thus, \( U_{CM} = P(\text{other players play a CM}) \cdot 0 + P(\text{at least one plays a CH}) \cdot v = (1 - P(\text{other players play a CM}) \cdot v = (1 - (1 - p)^{N-1}) \cdot v \). For equilibrium, the payoff \( U_{CH} \) and \( U_{CM} \) should be equal. Thus, \((v + c + r) = (1 - (1\)
Solving this equation, \( p = 1 - ((c - r)/v)^{1/(N-1)} \). Since \( c - r \) is positive and \( c - r < v \), let \( \theta = ((c - r)/v) \), then \( 0 < \theta < 1 \), and \( p = 1 - \theta^{1/(N-1)} \).

The reward mechanism has two functions. The first function is to encourage the sensor node to become a cluster head by increasing the probability of a player to be a CH, as explained earlier. While the first function has no direct consequence received by the cluster head, the second function is a ‘real’ reward. The second function of the reward is to allow the cluster head to be exempted from sensing and transmission activities. In other words, the sensor node that was a cluster head during the previous round receives a reward in the form of idle time. The duration of the idle time depends on its residual energy. That is, the sensor node that was a cluster head during the previous round is allowed to rest until its residual energy is almost the same as that of its neighboring nodes. By giving the cluster head the reward of idle time, the energy consumption among sensor nodes is more balanced and the network lifetime prolonged accordingly. It should be noticed that, because sensor nodes are redundantly deployed over the sensing area, a few sensor nodes could be excluded from the sensing activity without degrading network performance.

The duration of idle time is predicted by the sensor node itself, which was a cluster head during the previous round, without any control packet exchanges. The energy consumption of a sensor node to transmit data \( e_t \) and to receive data \( e_r \) is almost the same \( (e_t \approx e_r) \). At any one time, a cluster member only needs to send data once to the cluster head, whereas the cluster head needs to receive data from all its members. If a cluster head has \( M \) cluster members, then its energy consumption is roughly \( M \) times higher than that of its cluster members. The cluster head also has to perform data aggregation and data transmission to the sink. Thus, assuming that the neighboring sensor nodes were cluster members, the cluster head would collect its reward by being idle for the next \( M \) rounds so that, at the end of the idle time, the energy levels of the sensor nodes are similar.

The operation of CORE clustering is divided into rounds, where each round starts with a set-up phase to determine the cluster heads and is followed by a steady-state phase to transmit data [10]. In each round, the nodes calculate their probability of playing a CH, \( p \). In CORE clustering, the cost of being a cluster head is coupled with the residual energy contained in that node. If the residual energy of the node is relatively high, then the cost of being a cluster head is reduced. Consequently, if the residual energy of the node is relatively low, then the cost is increased. This setting is taken to support energy conservation as well as to extend network lifetime.

4. Performance Evaluation

4.1. Simulation Environment

A simulation using MATLAB was conducted to compare the performance of three clustering methods: probability-based, CROSS, and CORE. The probability-based clustering method has a fixed probability that a sensor node will be a cluster head. In the simulation, this probability was set at 0.05, as suggested in [10]. In CROSS, the probability that a sensor node will be a cluster head is dependent on parameter \( \omega \); that is, \( p = 1 - \omega^{1/(N-1)} \) and \( 0 < \omega < 1 \). The value of \( \omega \) was set at 0.5, as in the performance evaluation of [8]. For the proposed CORE clustering, the probability that a sensor node will be a cluster head is dependent on parameters \( r \) and \( c \), as in equation (3). The authors set \( r \) to be a fraction of \( c \), and \( c \) to be a fraction of \( v \). Additionally, the value of \( c \) was coupled with the residual energy of the sensor nodes, such that (i) when the sensor nodes have high residual energy, the cost of being a cluster head is low, and (ii) when the sensor nodes have low residual energy, the cost of being a cluster head is high. Given \( \alpha \) fraction of initial energy as the residual energy, the value of \( c \) is calculated by a simple subtraction: \( c = 1 - \alpha \).

The simulation settings are presented in Table 2. One round equals 100 sessions of data transmission from cluster members to their cluster heads, and for every 10 sessions, cluster heads aggregate the data received from the cluster members and sends them to the sink. It is assumed in the simulation that all sensor nodes are within each other’s transmission range.
4.2. Simulation Results and Discussion

Network lifetime using the three clustering methods is presented in Figure 2. Network lifetime is defined as the time it takes until exactly half of the sensor nodes are still alive. CORE outperforms both probability-based clustering and CROSS by 54.7% and 24.3%, respectively. This is because the cost and reward mechanisms in CORE clustering consider the residual energy of a sensor node and they support network load balancing, resulting in improved network lifetime. Figure 3 shows the average residual energy of the sensor nodes. Probability-based clustering and CROSS show similar outcomes, whereas CORE shows steadier and slower energy degradation.

![Figure 2. Network lifetime.](image)

The number of cluster heads determines the amount of data received by the sink, since the data collected by cluster members can be received by the sink only via the cluster heads. The amount of data sent to the sink is shown in Figure 4. CORE shows the highest value, which is 42.0% and 87.7% higher than probability-based clustering and CROSS, respectively. This is because, in CORE clustering, when the previous round has no cluster head, the sink will notice this event since no data was forwarded to it, and it will randomly force a sensor node to be a cluster head in the current round. This method ensures that there will be data collected by the sink during the current round and will increase the amount of data sent to the sink. While probability-based clustering and CROSS merely depend on each sensor node’s probability calculation for determining the existence of a cluster head, and they overlook the event of cluster head absence. Thus, in probability-based clustering and CROSS, the event of cluster head absence could occur continuously whereas, in CORE clustering, the event will not occur two times consecutively.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of sensors</td>
<td>100</td>
</tr>
<tr>
<td>Initial energy</td>
<td>0.5 J</td>
</tr>
<tr>
<td>Transmit energy</td>
<td>50 nJ</td>
</tr>
<tr>
<td>Receive energy</td>
<td>50 nJ</td>
</tr>
<tr>
<td>Transmit energy to the sink</td>
<td>100 nJ</td>
</tr>
<tr>
<td>Data aggregation energy</td>
<td>5 nJ</td>
</tr>
<tr>
<td>Packet size</td>
<td>800 bits</td>
</tr>
<tr>
<td>$r$</td>
<td>0.5$c$</td>
</tr>
</tbody>
</table>

Table 2. Simulation settings.
5. Conclusions

In this paper, a cost- and reward-based clustering method for wireless sensor networks is proposed, which aims to save energy and prolong network lifetime. Using game theory, CORE clustering determines the cost and rewards of being a cluster head and formulates the probability that a sensor node will declare itself a cluster head. The cost is coupled with residual energy, so the sensor nodes with high residual energy have a low cost from being a cluster head, and sensor nodes with low residual energy have a high cost from being a cluster head. The reward mechanism has two functions. The first is to encourage the sensor node to become a cluster head and the second is to allow the cluster head to be exempt from sensing and transmission activities. The authors compared the performance of CORE with both probability-based clustering and CROSS. The simulation results show that CORE outperforms both probability-based clustering and CROSS in terms of network lifetime and amount of data sent to the sink.
6. Acknowledgements

This paper is a technically revised and re-evaluated version of the preliminary in-progress report presented at the 22nd Wireless and Optical Communications Conference, May 2013 [11]. The authors wish to thank the editor and anonymous referees for their helpful comments for improving the quality of this paper. This research was supported in part by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (NRF-2013R1A1A2011744). Correspondence should be addressed to Dr. Sangman Moh (smmoh@chosun.ac.kr).

7. References