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Cooperative Clustering Algorithms for Wireless Sensor Networks

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1. Introduction

1.1 Wireless sensor networks

Wireless sensor networks have been made viable by the convergence of micro-electro-mechanical systems technology, wireless communications and digital electronics (Akyildiz et al., 2002). They are expected to consist of a large number of inexpensive sensor nodes, each having sensing, data processing and communicating components with limited computational and communication power. To provide various measurements such as light, temperature, pressure and activity, these low-cost, low-power, multifunctional sensor nodes have been widely deployed in a vast variety of environments for commercial, civil, and military applications such as surveillance, vehicle tracking, climate, etc.. However, a single sensor's view of the environment is restricted both in range and in accuracy, due to it only covers a limited physical area and may produce noisy data by the quality of the hardware. Accordingly, aggregation of the individual surveillance allows users to accurately and reliably monitor an environment.

Once sensor nodes are deployed throughout an area, they collect data from the environment and automatically establish dedicated networks to transmit their data to a base station. The nodes collaborate to gather data and extend the operating lifetime of the entire system. Wireless sensor networks offer a longevity, robustness, and ease of deployment that is ideal for environments where maintenance or battery replacement may be inconvenient or impossible (Hac, 2003). In recent years, with the rapid development of embedded systems including energy efficient devices, hardware/software co-design and networking support, sensor nodes have been smaller in size and more efficient in data processing and transmission. However, they are still limited in power, memory and computational capacities. As a result, the key challenge is to maximize the lifetime of sensor nodes due to the fact that it is not feasible to replace the batteries of thousands of nodes.

1.2 Clustering algorithms for wireless sensor networks

As one of the most widely investigated topology control mechanisms for wireless sensor networks, the clustering algorithm provides network scalability and energy efficient communications by reducing transmission overhead and enhancing transmission reliability. It can localize the route set up within the cluster and thus reduce the size of the routing table stored at the individual sensor node. Clustering can also conserve communication bandwidth since it limits the scope of inter-cluster interactions to cluster heads and avoids redundant exchange

of messages among sensor nodes (Younis et al., 2003). Moreover, clustering can stabilize the network topology at the level of sensor nodes and thus cuts on topology maintenance overhead (Abbasi & Younis, 2007).

The clustering protocols have been extensively proposed for achieving scalability through hierarchical approaches specifically for wireless sensor networks. In our research, we divide these clustering algorithms into self-configuring cluster formation and centralized cluster formation. In centralized cluster formation, the base station elects cluster heads each round to afford guarantee about the placement and number of cluster heads by a centralized clustering scenario. Hence, these protocols often need sensor nodes to be equipped with high-sensitivity global positioning system receivers for gathering position information of sensor nodes. In self-configuring cluster formation, each sensor node makes autonomous decisions itself using a distributed algorithm. The advantages of this approach are that no long-distance communication to the base station is required and distributed cluster formation can be done even without the exact location information of the sensor nodes in the network. In addition, no global communication is needed to set up the clusters and nothing is assumed about the current state of any other sensor node during cluster formation (Heinzelman, 2000).

In this chapter, we mainly concentrate on self-configuring cluster formation. In a clustering scheme, the network is partitioned into several clusters. Every cluster would have a leader, referred to as the cluster head. A cluster head is elected by the sensor nodes in a cluster for self-configuring cluster formation. A cluster head may be just one of the nodes or a node that is richer in resources. The cluster membership should be fixed or variable. After election, each cluster head broadcasts an advertisement message using carrier-sense multiple access for media access control protocol. Other nodes determine their cluster by the received signal strength of the advertisement messages, which is used as a measure of the required transmit power. Each non cluster head node determines which cluster it belongs to by choosing the cluster that requires the minimum communication energy. In a cluster, a cluster head gathers sensing data from all sensor nodes in the same cluster through a preset time division multiple access schedule and produces a condensed summary which is forwarded to the base station in each frame. A sensor node is associated with, at most, one cluster head and all communications are relayed through the cluster head.

The rest of this chapter is organized as follows. First of all, we introduce clustering algorithms for wireless sensor networks in Section 2. Then in Section 3, a cooperative game model for clustering in wireless sensor networks is presented for the nature of strategic interaction. Afterwards, we develop conditions to form cluster head coalitions and describe the cooperative game theoretic clustering algorithm in Section 4. Furthermore, as the results of simulation, we quantitatively analyze network lifetime, data transmission capacity and energy efficiency in Section 5. Finally, we draw conclusions in Section 6.

2. Previous Works

During recent years, a number of algorithms on self-configuring clustering had been presented for achieving energy efficiency. Low-Energy Adaptive Clustering Hierarchy (LEACH) (Heinzelman, 2000; Heinzelman et al., 2002) is an application-specific protocol architecture that forms clusters by a distributed algorithm. Cluster heads are burdened with a long-distance transmission to base station. Clustering explicitly encourages data aggregation to reduce the transmission burden in the network. This way, depending on the network configuration an increase of network lifetime can be accomplished (Hac, 2003). Afterwards, the low energy adaptive clustering hierarchy with deterministic cluster head selection (DCHS)

(Handy et al., 2002) extends LEACH's stochastic cluster head selection algorithm by a deterministic component and solves the problem of which the network is stuck after a certain number of rounds by a low cluster head selection threshold. Hybrid energy-efficient distributed clustering (HEED) (Younis & Fahmy, 2004) is a distributed scheme in which cluster heads are periodically selected according to a hybrid of the sensor node residual energy and communication cost. Recently, energy-efficient distance based clustering routing scheme (EEDBC) (Han et al., 2007) considers a distance from the base station to a cluster head and the residual energy as the criterion of the cluster head election for balance energy consumption among cluster heads. Therefore, this approach provides fully distributed manner and energy efficiency. In this section, we explain clustering algorithms which are widely investigated in the past few years.

2.1 Low-energy adaptive clustering hierarchy (LEACH)

LEACH is a protocol architecture for sensor networks that combines the ideas of energy-efficient cluster-based routing and media access together with application-specific data aggregation to achieve good performance in terms of system lifetime, latency and application-perceived quality (Heinzelman et al., 2002).

The operation of LEACH is divided into rounds. Each sensor node elects itself to be a cluster head at the beginning of round $r + 1$ (which starts at time t) with probability $P_i(t)$. $P_i(t)$ is chosen such that the expected number of cluster heads for this round is k. Thus, if there are N sensor nodes in the network, the expected number of cluster heads is:

$$E[number\ of\ cluster\ heads] = \sum_{i=1}^{N} P_i(t) = k.$$ (1)

Each sensor nodes to be a cluster head once in N/k rounds on average. $C_i(t)$ is denoted as the indicator function determining whether or not sensor node i has been a cluster head in the most recent ($r \bmod \frac{N}{k}$) rounds, then each sensor node should choose to become a cluster head at round r with probability:

$$P_i(t) = \begin{cases} \dfrac{k}{N - k(r \bmod \frac{N}{k})} & : C_i(t) = 1\ , \\ 0 & : C_i(t) = 0. \end{cases}$$ (2)

Therefore, only sensor nodes that have not already been cluster heads recently, and which presumably have more energy available than other sensor nodes that have recently performed this energy intensive function, may become cluster heads at round $r + 1$.

As shown in the flowchart of Fig. 1, LEACH processes as follows: once the sensor nodes have elected themselves to be cluster heads using the probabilities in (2), the cluster head should let all the other nodes in the network know that they have chosen this role for the current round. Therefore, each cluster head broadcasts an advertisement message. This message is a short message containing the node's ID and a header that distinguishes this message as an announcement message. Other nodes determine their clusters for this round by choosing the cluster heads that require the minimum communication energy, based on the received signal strength of the advertisement from each cluster head. Assuming symmetric propagation channels for pure signal strength, the cluster head advertisement heard with the largest signal strength is the cluster head that requires the minimum amount of transmit energy to communicate with. Note that typically this will be the cluster head closest to the sensor, unless

there is an obstacle impeding communication. In the case of ties, a random cluster head is chosen. After each sensor node has decided to which cluster it belongs, it informs the cluster head that it will be a member of the cluster. Each node transmits a join message back to the chosen cluster head. This message is again a short message, consisting of the node's ID and the cluster head's ID. The cluster heads in LEACH act as local control centers to coordinate the data transmissions in their cluster. The cluster head sets up a time division multiple access schedule and transmits this schedule to the sensor nodes in the cluster. This ensures that there are no collisions among data messages and also allows the radio components of each non cluster head to be turned off at all times except during their transmit time, thus reducing the energy consumed by the individual sensors. After the time division multiple access schedule is known by all sensor nodes in the cluster, the data transmission can begin. Fig. 2 shows an example of clusters formed in one round of LEACH. In this figure, each cluster has taken on a different color. In the cluster, the cluster head is denoted by a triangle. The position of base station is $(50, 175)$.
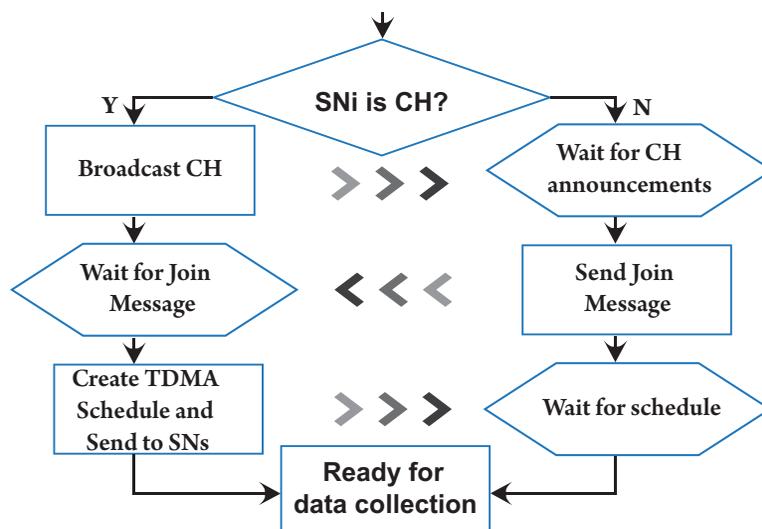

Fig. 1. Flowchart of LEACH procedure. (SN: sensor node; CH: cluster head)

2.2 Low energy adaptive clustering hierarchy with deterministic cluster head selection (DCHS)

DCHS is an energy-efficient clustering hierarchy protocol which is a modified version of the LEACH. Due to the inclusion of the residual energy level available in each sensor node, the approach increases the lifetime of a LEACH network. It can be achieved by (3), relative to the sensor node's residual energy. And this mechanism is expanded by a factor that increases the probability for any sensor node that has not been cluster head for the last k/N rounds.

$$P_i(t) = \frac{k}{N - k(r \bmod \frac{N}{k})} \left[\frac{E_{i\_res}}{E_{i\_ini}} + (r_s \mathrm{div} \frac{k}{N})(1 - \frac{E_{i\_res}}{E_{i\_ini}}) \right]. \tag{3}$$

with r_s as the number of consecutive rounds in which a sensor node has not been a cluster head. E_{i_res} and E_{i_ini} denote the residual and initial energy for sensor node i, respectively. Additionally, r_s is reset to 0 when a sensor node becomes a cluster head. For the deterministic selection of cluster heads only local and no global information is necessary. The nodes
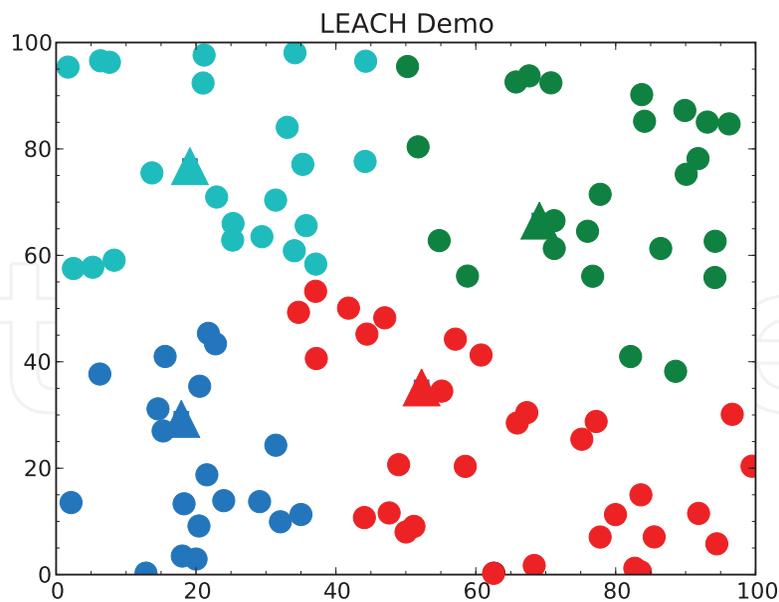
Fig. 2. The example: Cluster formation of LEACH in one round

determine themselves whether they become cluster heads. A transmission between the base station and a cluster head is not necessary.

2.3 Hybrid energy-efficient distributed clustering (HEED)

HEED considers a hybrid of energy and communication cost when selecting cluster heads. Unlike LEACH, it does not select cluster heads randomly. Only sensor nodes that have a high residual energy can become cluster heads (Abbasi & Younis, 2007). HEED has three main characteristics:

- To achieve well distribution of cluster heads in the network, the probability that two sensor nodes within each other's transmission range becoming cluster heads is small.

- Energy consumption is assumed to be multiform for all the sensor nodes.

- Within a given node's transmission range, the probability of cluster head selection can be adjusted to ensure inter cluster head connectivity.

In HEED, each sensor node is mapped to exactly one cluster and can directly communicate with its cluster head. The algorithm is divided into three phases:

1. Initialization phase: The algorithm first sets an initial percentage of cluster heads among all nodes. This percentage value, C_p, is used to limit the initial cluster head announcements to the other sensor nodes. Each sensor node sets its probability of becoming a cluster head, CH_p, as follows: $CH_p = C_p \times E_{res}/E_{ini}$, where E_{res} is the current energy in the node, and E_{ini} is the initial energy, which corresponds to a fully charged battery. CH_p is not allowed to fall below a certain threshold p_{min}, which is selected to be inversely proportional to E_{ini}.

2. Repetition phase: During this phase, every sensor node goes through several iterations until it finds the cluster head that it can transmit to with the least transmission power (cost). If it hears from no cluster head, the sensor node elects itself to be a cluster head and sends an announcement message to its neighbors informing them about the change of status. Finally, each sensor node doubles its CH_p value and goes to the next iteration

of this phase. It stops executing this phase when its CH_p reaches 1. Therefore, there are 2 types of cluster head status that a sensor node could announce to its neighbors:

- Tentative status: The sensor node becomes a tentative cluster head if its CH_p is less than 1. It can change its status to a regular sensor node at a later iteration if it finds a lower cost cluster head.

- Final status: The node permanently becomes a cluster head if its CH_p has reached 1.

3. Finalization phase: During this phase, each sensor node makes a final decision on its status. It either picks the least cost cluster head or pronounces itself as cluster head.

2.4 Energy-efficient distance based clustering (EEDBC)

EEDBC considers the uneven energy consumption of cluster heads which is resulted from uneven transmission cost between inter-cluster and intra-cluster communication due to the difference of distance to the base station. In other words, the basic ideal is that the closer to the base station, the larger cluster area. Therefore, each sensor node has the probability of becoming a cluster head which is determined by the distance to the base station and its residual energy.

$$P_i(t) = c \times \frac{d(S_i, BS) - d_{min}}{d_{max} - d_{min}} \times \frac{E_{i\_res}}{E_{i\_ini}}. \tag{4}$$

where c is a constant coefficient between 0 and 1, $d(S_i, BS)$ represents the distance between sensor node i and the base station, d_{max} represents the distance of the farthest sensor node from the base station and d_{min} represents the distance of the closest sensor node. E_{i_res} and E_{i_ini} denote the residual and initial energy for sensor node i, respectively. Fig. 3 shows an example of clusters formed in one round of EEDBC. In this figure, the denotation is same as the example of LEACH. We can find that the farther sensor nodes have higher probability to become cluster heads.
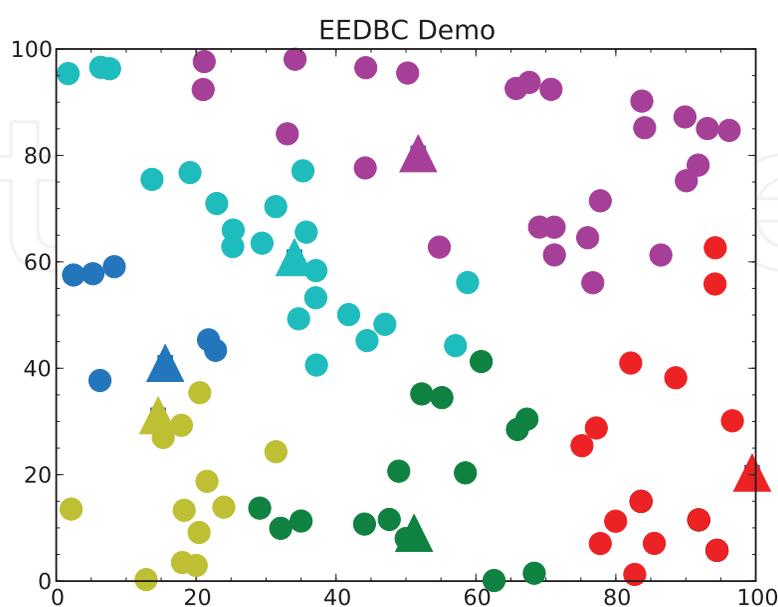

Fig. 3. The example: Cluster formation of EEDBC in one round

However, in the previous research, most of the game formulations for wireless sensor networks are non-cooperative games (Felegyhazi et al., 2006; Zheng et al., 2004), where sensor nodes act selfishly, to minimize their individual utility in a distributed decision-making environment (Machado & Tekinaya, 2008). Even if residual energy is utilized in the clustering algorithms, the behavior of sensor node is individual. Consequently, the network partition is expedited, and uneven residual energy is distributed across sensor nodes. In order to obtain global optimization, a cooperative game theoretic model is provided for balancing energy consumption of sensor nodes and increasing network lifetime and stability in this paper. Then, through the solution of the model, feasible cost allocations, we propose and analyze the cooperative clustering approach.

3. Cooperative Game Theoretic Model of Clustering Algorithms for Wireless Sensor Networks

3.1 Game and solution

Game theory is a mathematical basis for capturing behavior in interactive decision situation. It provides a framework and analytical approach for predicting the results of complex and dynamic interactions between rational agents who try to maximize personal payoff (or minimize private cost) according to strategies of other agents. The theory is generally divided into the non-cooperative game theory and the cooperative game theory. In non-cooperative games, the agents have distinct interests that interact by predefined mechanisms and deviate alone from a proposed solution, if it is in their interest, and do not themselves coordinate their moves in groups. In other words, for individually rational behaviors, they cannot reach an agreement or negotiate for cooperation. Contrarily, a cooperative game allows agents to communicate for allocating resources before making decisions by an unspecified mechanism. It is concerned with coalitions which are composed of group of agents for coordinating actions and feasible allocations. Cooperative game theory is concerned with situations when groups of agents coordinate their actions. Consequently, Cooperative games focus how to assign the total benefits (or cost) among coalitions, taking into account individual and group incentives, as well as various fairness properties (Nisan et al., 2007).

In this chapter, we mainly consider a cost sharing game which is a cooperative game concentrating on cost but not benefits. It is composed of a set $\mathcal{A}$ of n agents and a cost function c. Let $\mathbb{R}^+$ denote a set of nonnegative real numbers and $2^{\mathcal{A}}$ denote the set of all subsets of $\mathcal{A}$. We define the notion of a cost sharing game as follows:

Definition 3.1. (Cost Sharing Game) *A cost sharing game consists of a finite set $\mathcal{A}$ of n agents and a cost function c: $2^{\mathcal{A}} \longrightarrow \mathbb{R}^+$ to denote the nonnegative cost from the set of coalition.*

As a widely applicable concept, the Shapley value is a solution that assigns a single cost allocation to cost sharing games. We choose this solution to a cooperative game since the computational complexity is small and the Shapley value provides relatively anonymous solution by a random ordering of the agents. It had been proved that the Shapley value is the unique value on the set of games satisfying anonymity, dummy and additivity. Let $S \subseteq \mathcal{A} \setminus \{i\}$ denote all coalitions S of $\mathcal{A}$ not containing agent i. For any agent $i \in \mathcal{A}$ and any set $S \subseteq \mathcal{A} \setminus \{i\}$, the probability that the set of agents that come before i in a random ordering is precisely S is $s!(n-1-s)!/n!$, where $s = |S|$ is cardinality of S. Then the Shapley value ϕ on the cost

function c is represented by the following equation (5): For each agent i,

$$\phi_i(c) = \sum_{S \subseteq \mathcal{A} \setminus \{i\}} \frac{s!(n-1-s)!}{n!} (c(S \cup \{i\}) - c(S)) \tag{5}$$

where ϕ indicates the cost allocation in the cost sharing game $(\mathcal{A}, c)$.
Shapley value has three properties defined as follows:

- Anonymity: Even the agents change names, their cost shares do not change. Therefore, ϕ satisfies anonymity.

- Dummy: An agent who does not add to the cost should not be charged anything. Formally, if for every set $S \subseteq \mathcal{A} \setminus \{i\}$, $c(S) = c(S \cup \{i\})$, then $phi_i(c) = 0$.

- Additivity: For every two cost functions c_1 and c_2, $phi(c_1 + c_2) = phi(c_1) + phi(c_2)$, where $c_1 + c_2$ is the cost function defined by $(c_1 + c_2)(S) = c_1(S) + c_2(S)$.

3.2 Energy consumption model for wireless sensor networks

In various wireless sensor networks, to achieve maximum network lifetime, each sensor node should minimize the system energy dissipation through cooperation in our research. Therefore, for quantitative analysis of performance, we use a similar model applied in (Han et al., 2007; Handy et al., 2002; Heinzelman, 2000; Heinzelman et al., 2002) for the radio energy consumption where the transmitter consumes energy for radio electronics and power amplifier, and the receiver consumes energy for radio electronics in Fig.4.
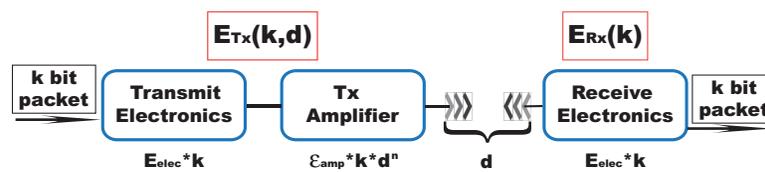

Fig. 4. Radio energy model

In radio propagation models, the free space propagation model (d^2 propagation loss) and the 2-ray ground reflection model (d^4 propagation loss) are used, according to the distance between the transmitter and receiver. The free space propagation model is used to predict received signal strength when the transmitter and receiver have a clear, unobstructed line-of-sight path between them. And the 2-ray ground reflection model is a useful propagation model that is based on geometric optics, and considers both the direct path and a ground reflected propagation path between transmitter and receiver. The cross-over distance between two propagation models is denoted by d_{co}. Power control can be used to invert the loss by setting the power amplifier to ensure a certain power at the receiver. Hence, the expressions for transmitting a message with l-bit over a distance d are:

$$E_{Tx}(l, d) = E_{Tx-elec}(l) + E_{Tx-amp}(l, d); \tag{6}$$

$$E_{Tx}(l, d) = \begin{cases} lE_{elec} + l\varepsilon_{fs}d^2 & : d < d_{co}, \\ lE_{elec} + l\varepsilon_{tr}d^4 & : d \geq d_{co}. \end{cases} \tag{7}$$

And the formula for receiving an l-bit message can be determined by:

$$E_{Rx}(l) = E_{Rx-elec}(l) = lE_{elec}. \tag{8}$$

For this model, the energy for data aggregation per bit is denoted by E_{DA}. For quantitative analysis, we assume that there are N sensor nodes distributed uniformly in a M×M region with k clusters, the length of each transmission data is l bits. Accordingly, the energy consumption of a cluster head in one frame can be expressed as:

$$E_{CH}(n) = l[n(E_{elec} + E_{DA}) + \varepsilon_{tr}d_{toBS}^4], \tag{9}$$

where d_{toBS} is the distance between the cluster head and base station, n is the sensor node number in each cluster. Moreover, each sensor node as non cluster head should send its sensing data to the cluster head. The energy dissipation of a non cluster head is presumed to follow the free space model. We assume that d_{toCH} is the distance between the sensor node and the cluster head in the same cluster. Thus, the energy consumption of a non cluster head is:

$$E_{non-CH}(d_{toCH}) = l[E_{elec} + \varepsilon_{fs}d_{toCH}^2]. \tag{10}$$

Then if we assume the area of a cluster is a circle with radius $R = M/\sqrt{k\pi}$ and the cluster head is at the center of the cluster, the expected value of d_{toCH}^2 is derived from (Heinzelman et al., 2002) as follows:

$$E[d_{toCH}^2(k)] = \frac{M^2}{2k\pi}. \tag{11}$$

3.3 Cooperative game theoretic model of clustering

To understand the effect of energy and transmission cost on the clustering, in this paper, we consider the cost sharing game with 3-agents. In the case shown in Fig. 5, the CCH is assumed as the candidate cluster header. We consider the CCH_E and the CCH_D with the redundant energy and the distance from the CCH, respectively. We define this cost sharing game as follows:
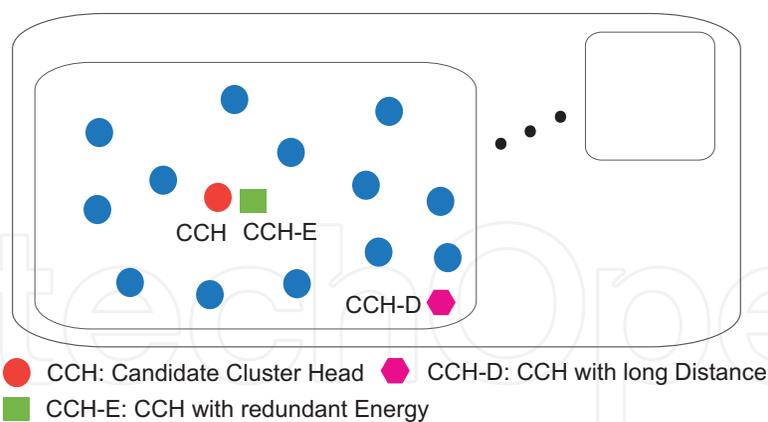

Fig. 5. Cluster architecture for cooperation

Definition 3.2. (Cost Sharing Game for Clustering) *Let $(\mathcal{A}, c)$ be a cost sharing game for clustering in wireless sensor networks. The set of $\mathcal{A} = \{CCH, CCH\_E, CCH\_D\}$ of 3-agents is the candidate cluster headers set. For a coalition set $S \subseteq \mathcal{A}$, the cost function of this coalition is defined as the total energy consumption of all sensor nodes for data collection in one round involving β frames while each agent in S is as a cluster header. Moreover, when chosen as a cluster header, the CCH_E consume the redundant energy firstly. Correspondingly, the total cost should subtract the redundant energy of CCH_E.*

As one of the properties of the Shapley value, anonymity represents that changing the names of agents does not change their cost shares. In order to concentrate on impact on system-wide optimization, we assume that the CCH_E with redundant energy (E_{red}) is close to the CCH and the CCH_D is the farthest sensor node from CCH. Therefore, if the CCH_E is elected as a cluster header, the distance from sensor nodes to cluster header d_k is the same as the value d_{toCH} deduced from k clusters in (11). Contrarily, if the CCH_D is as one of cluster headers, at this time, the distance from sensor nodes to cluster heads d_{2k} should be d_{toCH} derived from $2k$ clusters in the whole region. We denote a coalition of candidate cluster heads as S. Wherefore, the cost function defined by this instance is the following:

$$c(S) = \beta c_{CH}(S) + \beta c_{non-CH}(S) + c_{red}(S); \tag{12}$$

and we assume that $c(\varnothing) = 0$. $c_{CH}(S)$ represents the energy consumption of all cluster heads in S. It can be written as $c_{CH}(S) = sE_{CH}(n/s)$. $c_{non-CH}(S)$ is the energy consumption of all non cluster heads when agents in S are as cluster heads. We can obtain $c_{non-CH}(S)$ as:

$$\begin{cases} (n-s)E_{non-CH}(d_{2k}) & : s > 1 \text{ and } CCH\_D \in S, \\ (n-s-1)E_{non-CH}(d_k) + E_{Tx}(l,d) & : \text{otherwise,} \end{cases} \tag{13}$$

where $s = |S|$ and $E_{Tx}(l,d)$ is transmission energy consumption over the distance between the CCH and the CCH_D. $c_{red}(S)$ represents the redundant energy of the CCH_E when $CCH\_E \in S$. Therefore, we have:

$$c_{red}(S) = \begin{cases} -E_{red} & : CCH\_E \in S, \tag{14a} \\ 0 & : \text{otherwise.} \tag{14b} \end{cases}$$

We consider the cost sharing game for clustering expressed in Definition 3.2. The solution of this game ($\phi_{CCH}, \phi_{CCH\_E}, \phi_{CCH\_D}$) is figured out by the Shapley value from (5). The objective of the model is to achieve global optimization of energy consumption from coalitions of cluster heads. In other words, the solution describes an approach to the fair allocation of cost obtained by cooperation among agents of candidate cluster heads in clustering. Therefore, the fair way to allocate system cost is to allocate energy consumption from each agent considering the capacity of redundant energy and transmission energy. For example, since $\phi_{CCH} + \phi_{CCH\_E} + \phi_{CCH\_D} = c(\{CCH, CCH\_E, CCH\_D\})$, ϕ_{CCH_D} can be described as the fair energy cost allocation of all nodes in the cluster while the CCH_D is elected as a cluster head considering its transmission cost.

4. A Novel Cooperative Clustering Algorithm

4.1 Basic idea

According to the cost allocations from the cost sharing game for clustering, we present the cooperative game theoretic clustering algorithm (CGC) in this section. Different from previous non-cooperative clustering algorithms, our basic idea is that sensor nodes should trade off individual cost with network-wide cost. Consequently, a CCH should cooperate with other capable sensor nodes to form a coalition as cluster heads considering number of sensor nodes in a cluster, the redundant energy and the transmission energy.

4.2 Conditions of cooperation

All sensor nodes participate in the cluster head selection process through our scheme. In the end, competent sensor nodes are elected as cluster heads. If there are no partners, the candidate cluster head is decided to accomplish data collection in the round by itself. At this time, the system energy consumption is $c(\{CCH\})$. Therefore, we can derive conditions of coalitions as follows:

- Cooperate with a sensor node with redundant energy:
  $\phi_{CCH} + \phi_{CCH\_E} < c(\{CCH\})$;
- Cooperate with a sensor node with long distance:
  $\phi_{CCH} + \phi_{CCH\_D} < c(\{CCH\})$.

4.3 Cooperative game theoretic clustering algorithm (CGC)
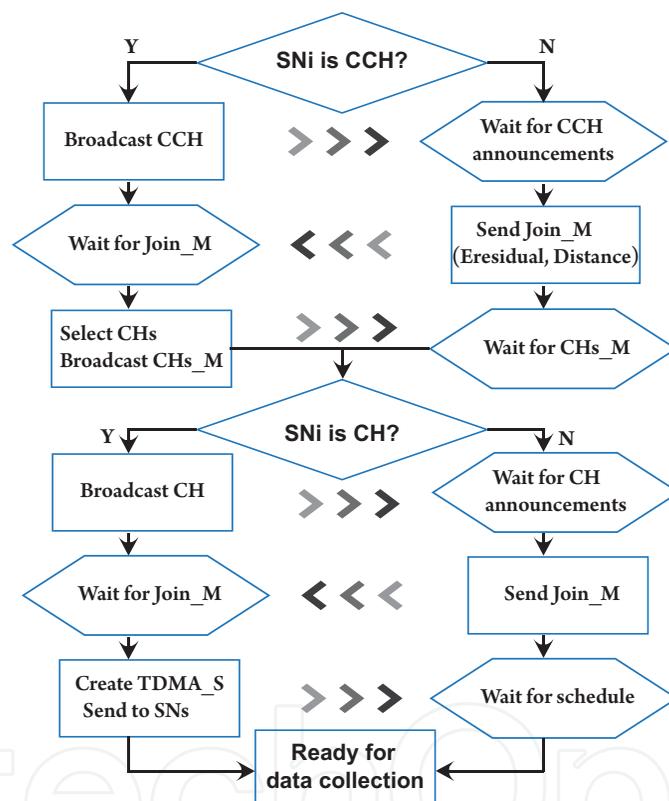
Fig. 6. Flowchart of CGC procedure

As shown in the flowchart of Fig. 6, the CGC processes as follows: at the beginning of round r, each sensor node elects itself to be a candidate cluster head with probability $P_i = \frac{k}{N-k*(r mod \frac{N}{k})} \frac{E_{residual}}{E_{initial}}$, which is the similar with DCHS (Handy et al., 2002). Then each CCH broadcasts an advertisement message by carrier-sense multiple access protocol to let other sensor nodes choose the optimum cluster due to received signal strength. Thus, these announcements must be broadcast to reach all of sensor nodes in the area. Afterwards, each non-CCH node sends the join message including sensor node's ID, the residual energy and the distance from the CCH to be concerned with cluster head election. After receiving all join messages of non-CCHs in a cluster, a CCH could adjust the final coalition of cluster heads according to conditions of cooperation mentioned in Section 4.2, where for sensor node i,

$E_{red\_i} = E_{residual\_i} - E_{residual\_CCH}$. Then a CCH broadcasts the set ID of cluster heads, and other sensor nodes listen and wait for the reception of cluster head coalition message. If selected as a cluster head, a sensor node would broadcast an advertisement message to inform other nodes in the network of its decision. Otherwise, non-CHs wait for cluster head announcements and choose the optimum cluster. With that, each non cluster head node sends the join message to the cluster head which is chosen through received signal strength. After receiving all join messages in a cluster, a cluster head creates a time division multiple access schedule according to number of sensor nodes in the current cluster. Finally, it transmits this schedule to ensure that there are no collisions among data transmission and non cluster heads could decrease energy consumption during idle time. After receiving time division multiple access schedules, all sensor nodes get sensing data and transmit it to cluster heads during their allocated time slots. For data collection, cluster heads aggregate individual data from each non cluster head and send condensed summaries to the base station.

5. Simulation and Analysis

In this section, we describe the simulation environment and the analysis of results. Our simulation is based on ns2 and LEACH (Heinzelman, 2000; Heinzelman et al., 2002). The simulation scenarios consist of simplex energy distribution with different position distribution. In the simplex scenarios, the position of each sensor node is random, lattice, semi-lattice and normal distribution, respectively. In the semi-lattice distribution, half of sensor nodes are distributed with lattice method; the others are randomly distributed in the area. Moreover, Fig. 7 and 8 provide a detailed analysis of the simplex scenario with random distribution in the best case. We also present a statistical analysis of other results with the 0.975 confidence in Fig. 9 and 10.

Table 1. Simulation parameter values

Parameter	Value
N	100
M	100m
k	5
d_{co}	86.4m
ε_{fs}	3×10^{-12}J/bit/m^2
ε_{tr}	4×10^{-16}J/bit/m^4
R_b	1Mbps
E_{elec}	0.5nJ/bit
E_{DA}	0.1nJ/bit

5.1 Simulation set-up

In (Daly & Chandrakasan, 2007), a 1Mbps 916.5MHz on-off keying (OOK) transceiver for wireless sensor networks had been designed in a 0.18-μm CMOS process. The minimal receiver power consumption is 0.5mW. Moreover, the noise figure of the Radio Frequency front-end including the 3.5dB loss of the surface acoustic wave (SAW) filter is between 14dB and 15dB for all gain settings, indicating that the tuned low noise amplifier (LNA) dominates the noise figure. Therefore, in our simulation, we set E_{elec} is 0.5nJ/bit for a bit rate (R_b) 1Mbps transceiver,

the thermal noise floor is 99dBm, the receiver noise figure is 14dB and a signal-to-noise ratio(SNR) is at least 28dB to receive the signal with no errors. Thus, the minimum receive power $P_{r-thresh}$ for successful reception is $P_{r-thresh} \leq -57$dBm. With that, the cross-over distance d_{co} is 86.4m. And in (7), ε_{fs} and ε_{tr} are 3×10^{-12}J/bit/m^2 and 4×10^{-16}J/bit/m^4, respectively. Furthermore, the ARM (Advanced RISC Machine) architecture is widely used in embedded designs. For power saving features, ARM CPUs are dominant in wireless sensor networks, where low power consumption is a critical design goal. In recent years, the new version of ARM has been successfully used for many years in a wide range of wireless device application. Building on the Cortex foundation, the processor achieves performance of 2.0DMIPS/MHz, low power of 0.5mW/MHz and speed up to 1GHz. Thus, we assume that the energy consumption of per bit data aggregation (E_{DA}) is 0.1nJ/bit. For our simulation, we assume that 100 sensor nodes are dispersed into the 100m×100m area with 5 clusters and the simulation is finished when the rate of sensor nodes alive is less than 0.1.
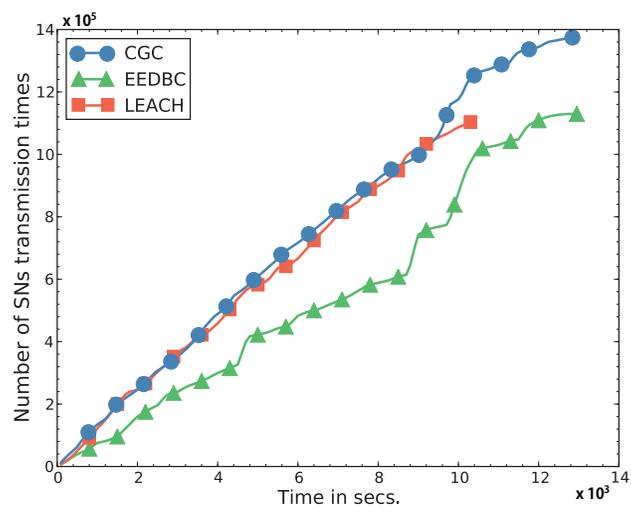
Fig. 7. Lifetime and data capacity
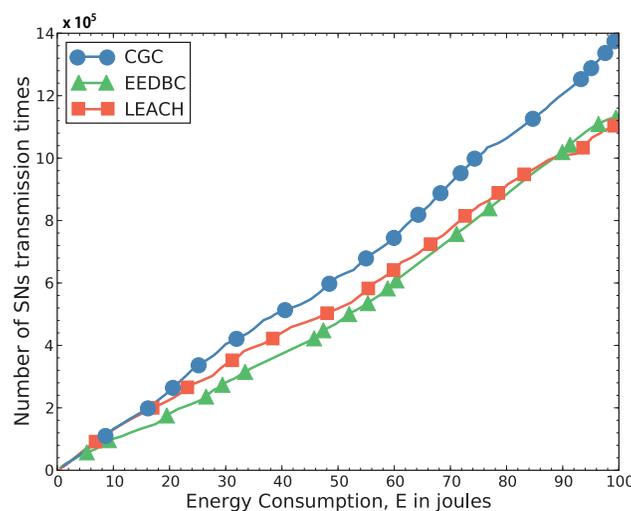
Fig. 8. Energy efficiency

5.2 Analysis of simulation results

In this section, we introduce the results of simplex scenario while the initial energy of a sensor node is 1J and the position of base station is $(50, 175)$. In our simulation, we use the number of sensor nodes transmission times defined as the sum of transmission times for each sensor node to represent the data transmission capacity. The effect of capacity of data transmission on the time is shown in Fig. 7. As illustrated in this figure, both in CGC and EEDBC, the network lifetimes are greatly prolonged more than that of LEACH about 25%. Typically, however, the final number of sensor nodes transmission times is increasing up to 24.5% and 21.6% compared with LEACH and EEDBC, respectively. Accordingly, at the same time, our scheme provides more amount of transmission data to base station. In other words, CGC also reduces the data transmission latency. Fig. 8 compares the three algorithms in terms of energy efficiency defined as the number of sensor nodes transmission times per unit energy. The result shows that CGC is the most efficient scheme and the transmission data per unit energy is delivered up to approximate 22% in the end.
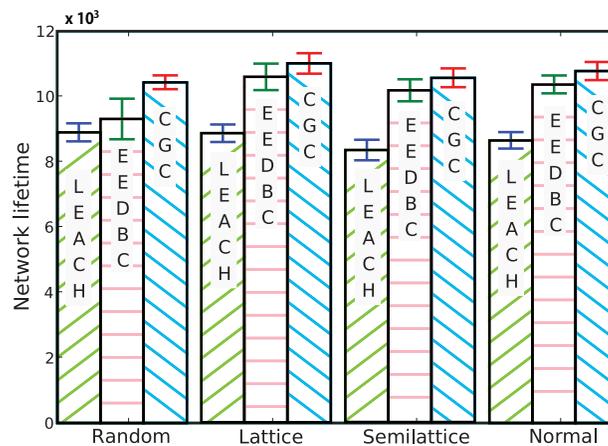
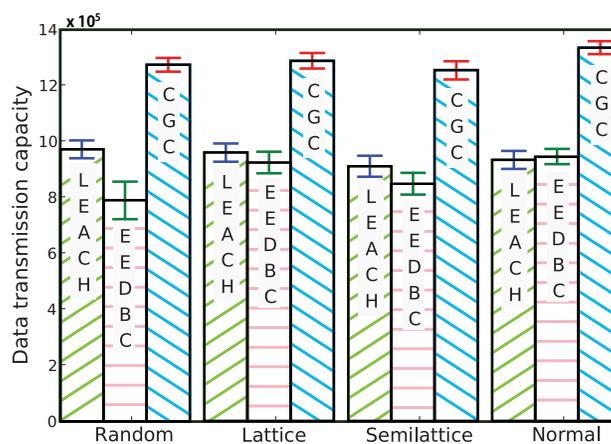

Fig. 9. Statistical analysis of lifetime

Fig. 10. Statistical analysis of data capacity

From the statistical analysis of network lifetime in Fig. 9 and data transmission capacity in Fig. 10, comparing with other approaches, our scheme can guarantee to prolong network lifetime and improve data transmission capacity up to 5.8% and 35.9%, respectively.

The results of simulation show that CGC outperforms other algorithms on network lifetime, data transmission capacity and energy efficiency with concern of position distributions. Therefore, our scheme can surely guarantee to prolong network lifetime, reduce data transmission latency and improve the utilization of energy.

6. Conclusion

In this chapter, we presented a cooperative game theoretic model for clustering algorithms in wireless sensor networks, which is provided for balancing energy consumption of sensor nodes and increasing network lifetime and stability. Moreover, from feasible allocations of energy cost as the results of this model, we proposed and analyzed the cooperative clustering algorithm to obtain system-wide optimization from conditions of cooperation, considering the redundant energy, communication costs and number of sensor nodes in a cluster adapting to various wireless sensor networks. The basic idea is that each sensor node should trade off individual cost with network-wide cost. Consequently, each capable sensor node should cooperate with others in cluster formation for collective decision-making. Furthermore, we presented performance evaluation and comparison of the existing clustering algorithms with our approach quantitatively with respect to network lifetime, data transmission capacity and energy efficiency. We provided a detailed analysis of the simplex scenario with random position distribution in the best case and a statistical analysis of the scenarios with different position distributions including random, lattice, semi-lattice and normal distributions. Comparing with other approaches through simulations, our protocol can surely guarantee to prolong network lifetime and improve data transmission capacity up to 5.8% and 35.9%, respectively.

7. References

Abbasi, A. A. & Younis, M. (2007). A survey on clustering algorithms for wireless sensor networks, *Computer Communications* **Vol. 30**(No. 14-15): 2826–2841.

Akyildiz, I., Su, W., Sankarasubramaniam, Y. & Cayirci, E. (2002). Wireless sensor networks: a survey, *Computer Networks: The International Journal of Computer and Telecommunications Networking* **Vol. 38**(No. 4): 393–422.

Daly, D. & Chandrakasan, A. (2007). An energy-efficient ook transceiver for wireless sensor networks, *IEEE Journal Solid-State Circuits* **Vol. 42**(No. 5): 1003–1011.

Felegyhazi, M., Hubaux, J.-P. & Buttyan, L. (2006). Nash equilibria of packet forwarding strategies in wireless ad hoc networks, *IEEE Transactions on Mobile Computing* **Vol. 5**(No. 5): 463–476.

Hac, A. (2003). *Wireless Sensor Network Designs*, John Wiley and Sons.

Han, Y., Park, S., Eom, J. & Chung, T. (2007). Energy-efficient distance based clustering routing scheme for wireless sensor networks, *Lecture Notes in Computer Science, Computational Science and Its Applications* **Vol. 4706/2007**: 195–206.

Handy, M. J., Haase, M. & Timmermann, D. (2002). Low energy adaptive clustering hierarchy with deterministic cluster-head selection, *Proceedings of 4th IEEE Conference on mobile and wireless communications network*, pp. 368–372.

Heinzelman, W. (2000). Application-specific protocol architectures for wireless networks, *Ph.D. thesis, Massachusetts Institute of Technology* .

Heinzelman, W., Chandrakasan, A. & Balakrishnan, H. (2002). An application-specific protocol architecture for wireless microsensor networks, *IEEE Transactions on Wireless Communications* **Vol. 1**(No. 14): 660–670.

Machado, R. & Tekinaya, S. (2008). A survey of game-theoretic approaches in wireless sensor networks, *Computer Networks: The International Journal of Computer and Telecommunications Networking* **Vol. 52**(No. 16): 3047–3061.

Nisan, N., Roughgarden, T., Tardos, E. & Vazirani, V. V. (2007). *Algorithmic Game Theory*, Cambridge University Press.

Younis, M., Youssef, M. & Arisha, K. (2003). Energy-aware management for cluster-based sensor networks, *Computer Networks* **Vol. 43**(No. 5): 649–668.

Younis, O. & Fahmy, S. (2004). Heed: A hybrid, energy-efficient, distributed clustering approach for ad hoc sensor networks, *IEEE Transactions on Mobile Computing* **Vol. 2**(No. 4): 366–379.

Zheng, Z., Wu, Z. & Lin, H. (2004). Clustering routing algorithm using game-theoretic techniques for wsns, *Proceedings of the 2004 international symposium on circuits and systems*, pp. IV–904–7.
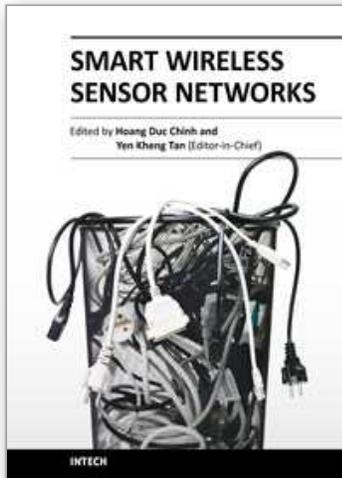
Smart Wireless Sensor Networks

Edited by Yen Kheng Tan

The recent development of communication and sensor technology results in the growth of a new attractive and challenging area – wireless sensor networks (WSNs). A wireless sensor network which consists of a large number of sensor nodes is deployed in environmental fields to serve various applications. Facilitated with the ability of wireless communication and intelligent computation, these nodes become smart sensors which do not only perceive ambient physical parameters but also be able to process information, cooperate with each other and self-organize into the network. These new features assist the sensor nodes as well as the network to operate more efficiently in terms of both data acquisition and energy consumption. Special purposes of the applications require design and operation of WSNs different from conventional networks such as the internet. The network design must take into account of the objectives of specific applications. The nature of deployed environment must be considered. The limited of sensor nodes' resources such as memory, computational ability, communication bandwidth and energy source are the challenges in network design. A smart wireless sensor network must be able to deal with these constraints as well as to guarantee the connectivity, coverage, reliability and security of network's operation for a maximized lifetime. This book discusses various aspects of designing such smart wireless sensor networks. Main topics includes: design methodologies, network protocols and algorithms, quality of service management, coverage optimization, time synchronization and security techniques for sensor networks.

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