Genetic Algorithmic Topology Control for Two-Tiered Wireless Sensor Networks^{*}

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Abstract. This paper proposes an optimized topology control scheme (GA-OTC) based on a genetic algorithm for clustering-based hierarchical wireless sensor networks (WSNs). By using a genetic algorithm, we can obtain optimal solutions to multiple objective functions according to the two criteria of both balanced energy consumption and minimized total energy consumption of cluster heads while the entire WSNs field is covered by clusters. Through performance evaluation studies, we show that *GA-OTC* achieves desirable properties.

Keywords: GA-OTC, WSNs, multiple objective functions.

1 Introduction

In recent years, many researches on wireless sensor networks (WSNs) have become one of the active research topics in wireless networking technologies [1]. Sensor nodes (SNs), the main components of WSNs, are deployed over the networked sensing fields, and perform specific tasks with the data processing, event sensing, and data communicating [1]. Due to their limited power source, energy consumption has become the most critical factor when designing WSNs protocols. Facing these challenges, several schemes to prolong the lifetime of WSNs, including clustering-based topology control, have been investigated [2]-[9]. By using an efficient clustering-based topology control algorithm, several advantages can be obtained, i.e., (1) improving network connectivity and capacity, (2) improving spatial reuse, and (3) mitigating the MAC-level medium contention [2]-[4]. The clustering-based WSNs can be classified into two types [3]: i.e., homogeneous one and heterogeneous one. In homogeneous clustering-based WSNs [5][6], by all SNs have same architectures, the algorithm for cluster head (CH) election is required because the CH must be chosen among SNs. In this structure, each SN has the function for clustering which can be a burden to the hardware constrained SNs. On the other hand, in non-homogeneous clustering-based WSNs [7]-[9], different types of nodes are used for CH-role. Therefore a node which has a functionality of the CH has more computing power than

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SNs which is not the CHs. The non-homogeneous clustering-based WSNs, therefore, can achieve more energy-efficiency. In this paper, the non-homogeneous clustering-based WSNs is considered as a reference network model. In WSNs, balance energy consumption and minimized total energy consumption are required among CHs to prolong network lifetime [4][9]. To achieve the desired properties, the method of regulating cluster radii is effective as shown in [4][9]. As a method of regulating cluster radii, genetic algorithmic approach is used in this paper. By using a genetic algorithm, the most notable optimization method, we can achieve effective performance in regulating cluster radii to obtain optimal solutions.

The remainder of this paper is organized as follows. Section 2 shows related work. Section 3 describes our proposed algorithm. Section 4 shows performance results. Finally, section 5 concludes this paper and shows future work direction.

2 Related Work

Clustering-based WSNs can be classified into two types [3]: i.e., homogeneous clustering-based WSNs and hierarchical clustering-based WSNs. In homogeneous clustering-based WSNs, the algorithm for cluster head election is required because the CH must be chosen among SNs. Therefore, SNs must have the functionality for clustering and controlling their clusters. This functionality of SNs must be a burden to the hardware constrained SNs. On the other hand, in hierarchical clustering-based WSNs [3][8][9], different types of SNs are used. A mobile node with the functionality of CH has more computing power than a SN which is not the CH. The hierarchical clustering-based WSNs, therefore, can achieve more energy-efficiency. There are numerous topology control algorithms for hierarchical clustering-based WSNs [7]-[9]. The proposed algorithm in [7] uses three kinds of SNs for energy-efficiency. However the proposed scheme in [7] must maintain global information. It can be a burden to CHs. Therefore, decentralized scheme is required in resource-constrained WSNs. The proposed scheme in [8] has a two-tiered WSNs architecture. In the upper tier, there are CHs and in the lower tier, typical SNs. In [8], however, the radii of clusters are fixed. In this system, the performance of scheme depends on each radius of the cluster. That is to say, it can be a waste of energy when a cluster has a larger radius than required. On the other hand, if a cluster has a smaller radius than required, it cannot guarantee perfect coverage, means there is no area uncontrolled by a CH in the networked sensing field. Therefore, maintaining the optimal cluster radius is important. However, it is impossible for [8], which has a fixed radius system, to regulate the cluster radius. On the other hand, our previous work, i.e., LLC [9] can regulate the cluster radius for energy efficiency in WSNs. However in LLC, there exists a maximum radius problem which can lead energy-inefficiency in some network topology due to the assumption of the circularity of cluster radius. With genetic algorithmic approach, the proposed scheme in this paper, we can overcome maximum radius problem and achieve better performance.

Fig. 1. Examples of the grid which is assigned to 3 CHs and initial population (4 CHs)

3 Genetic Algorithmic Optimized Topology Control (*GA-OTC*)

The aim of *GA-OTC* is to propose an algorithm which covers all SNs and considers energy consumption by a genetic algorithm. *GA-OTC* balances and minimizes energy consumption of CHs. A sensor field which needs covering with CHs is segmented by a grid form. SNs are located in any point of each grid cell. Once a grid cell is assigned to CH, CH communicates with SNs located in a grid cell as shown in Fig. 1. The group of grid cells assigned to a CH is defined as a clustering area.

3.1 Energy Model of a Wireless Device

To describe *GA-OTC*, the energy model of a CH can be formulated as follows.

$$E = E_{communicating} + E_{processing} \quad (1)$$

Energy consumption on data communicating. Assuming an $1/d^2$ path loss, where d is the distance between a CH and an SN, the energy consumed when transmitting and receiving data are Eq. (2) and Eq. (3).

$$E_{tx} = (\alpha_t + \alpha_{amp} \cdot d^2) \cdot n \quad (2)$$

$$E_{rx} = \alpha_r \cdot n \quad (3)$$

α_t , α_{amp} , and α_r are the energy/bit consumed by transmitter, transmitter op-amp, and receiver. The total energy consumption on data communicating is composed by E_{tx} and E_{rx} as shown in Eq. (4).

$$E_{communicating} = E_{tx} + E_{rx} \quad (4)$$

Energy consumption on data processing. In general, the energy consumption on data processing is significantly smaller than the energy consumption on data communication. Therefore the energy consumption can be ignored.

3.2 Problem Formulation

We define a clustering set that a sensor j belongs to the clustering set of CH, i.e., C_i , for all sensors. Using an energy model for a CH denoted in section 3.2, the communication energy (CE) between C_i and j , denoted as CE_{j,C_i} , is calculated as follows.

$$CE_{j,C_i} = E_{tx} + E_{rx} = (\alpha_t + \alpha_{amp} \cdot d_{j \rightarrow C_i}^2) \cdot n + \alpha_r \cdot n \quad (5)$$

where $d_{j \rightarrow C_i}$ is the distance between j and C_i . Energy consumption of each CH by every SN of its clustering set is calculated by adding up energy consumption of all sensors in each clustering set, denoted as EC_{C_i} .

$$EC_{C_i} = \sum_{j \in C_i} CE_{j,C_i} \quad (6)$$

Thus, the variance and average of energy consumption of CHs can be shown as Eq. (7) and Eq. (8).

$$\mathcal{V}(C) = \frac{1}{r} \sum_{i=0}^r (EC_{C_i} - \mathcal{A}(C)) \quad (7)$$

$$\mathcal{A}(C) = \frac{1}{r} \sum_{i=0}^r EC_{C_i} \quad (8)$$

where r is the number of CHs. C is a vector that consists of set variables $(C_1, C_2, \dots, C_r)$. $\mathcal{V}$ and $\mathcal{A}$ are functions of C which denote variance and average of energy consumption. Let us denote all possible solution space of C to Ω , now we can construct objective functions for minimizing both variance and average of energy consumption of CHs.

$$\arg \min_{C \in \Omega} \mathcal{V}(C) \quad (9)$$

$$\arg \min_{C \in \Omega} \mathcal{A}(C) \quad (10)$$

3.3 Topology Control Procedure

Initial population. Each P chromosome is set as follows. To assign grid cells to each CH continuously, we use probabilistic iteration based in grassfire concept [12]. In this paper, we use propagation probability of grid cells instead of threshold of grassfire concept. Probabilistic propagation starts in every initial cell, where CH is located, and continues until all the cells are assigned to CHs as shown in Fig. 1.

Fitness computation. The fitness computation is designed with genetic algorithm. The proposed scheme in this paper uses simple additive weighting method [13]. The objective function of multi-objective problem consists of the sum of weighted objective functions. The fitness computation function by using simple additive weighting method is shown in Eq. (13), which is derived by Eq. (11) and Eq. (12).

$$f_v = \frac{1}{\sigma} = \frac{1}{\sqrt{\mathcal{V}}} = \frac{1}{\sqrt{\frac{1}{r} \sum_{i=0}^r (EC_{C_i} - \mathcal{A}(C))}} \quad (11)$$

$$f_a = \frac{1}{\mathcal{A}} = \frac{1}{\sqrt{\frac{1}{r} \sum_{i=0}^r (EC_{C_i})}} \quad (12)$$

$$F = w_v \cdot f_v + w_a \cdot f_a \quad (13)$$

where w_v and w_a are the weight values for determining which to be optimized. The summation of weight values has to be one. We use simple additive method described above instead of the pareto method, another well-known scheme which determines optimal solution. The pareto method uses dominant-nondominant relationships between solutions. However, this method is not appropriate to use to determine which objective to optimize.

Selection. In this paper, we use roulette wheel selection, a common technique that implements the proportional selection strategy. In roulette wheel selection scheme which resembles survival of the fittest in nature, the chance to be selected for the reproduction of a chromosome is determined by its ratio of fitness value.

Crossover. The crossover process is a probabilistic process which exchanges information between two parent chromosomes to generate two child chromosomes. We use the crossover process which child chromosomes inherit one section from each of parent chromosomes partitioned by random partitioning. This crossover process might violate basic assignment principle defined as the continuous cell assignment, which is assumed in initial population. However, if the fitness of such a chromosome is low, it is dismissed in selection process. In this way, crossover process helps algorithm converge into optimal solution as it guarantees the variety of populations.

Mutation. The mutation process in this paper is computed by exchanging of boundary cells assigned to each CHs.

Optimal solution and terminal criterion. The process of fitness computation, selection, crossover, and mutation is executed for a maximum number of iterations. We use an elitist strategy to preserve the best parent chromosome. Therefore a parent chromosome with the highest fitness is always copied into the next generation.

Fig. 2. Standard deviation of load with varying density (5 CHs)

4 Performance Evaluation

The performance evaluation of *GA-OTC* algorithm is shown in the aspect of (1) balanced energy consumption among CHs and (2) minimized total energy consumption. We plot the results obtained from our simulation in Fig. 2 and 3. To evaluate our algorithm, we compare the results of the proposed scheme with shortest distance based algorithm and Low-Energy Localized Clustering (LLC) algorithm [9]. In shortest distance based algorithm a CH includes an SN in its cluster if the distance between them is the minimum. LLC algorithm is the algorithm which regulates the cluster radius for energy efficiency.

4.1 Balanced Energy Consumption

The graph shown in Fig. 2. indicates that *GA-OTC* algorithm achieves clearly lower standard deviation with increase in density. Results demonstrate that our approach *GA-OTC* with $w_v=0.8$, $w_a=0.2$ and *GA-OTC* with $w_v=0.2$, $w_a=0.8$ is better than shortest distance based algorithm and LLC algorithm. In LLC, it causes ineffective radius problem compared to our algorithm. Because LLC selects maximum radius to cover all sensor fields and its' clustering radii of CHs are fixed to circle.

4.2 Minimized Total Energy Consumption

Average energy consumption on a CH will be minimum when shortest distance based algorithm is used but the load will not be balanced. We try to minimize the average energy consumption as good as shortest distance based algorithm with increase in CHs. As shown in Fig. 3, *GA-OTC* with $w_v=0.2$, $w_a=0.8$ performs better than LLC and *GA-OTC* with $w_v=0.8$, $w_a=0.2$. *GA-OTC* with $w_v=0.8$, $w_a=0.2$ performs worse than LLC and *GA-OTC* with $w_v=0.2$, $w_a=0.8$ since

Fig. 3. Average energy consumption on a CH (300 SNs)

Fig. 4. Standard deviation of load and average communication energy on a CH with varying weight policy (5 CHs, 300 SNs, normalized with respect to the highest value)

weight factors of it is focused on minimizing the variance rather than average of energy consumption. Two demonstrated results are based on the aspect of two weight policies. When $w_v=0.2$, $w_a=0.8$, weight of minimized total energy consumption is greater than weight of balanced energy consumption, results indicate that the average is better than $w_v=0.2$, $w_a=0.8$ and vice versa. The graph shown in Fig. 4. clearly describes the tendency of the standard deviation and average communication energy reflected by various weight policies. The values on the counter domain are normalized with respect to the highest value. This weight policy can be implemented to optimize various environments of WSNs by changing weight factors. For example, in some WSNs, the survival of every node can be the most important mission. In these cases, we can achieve longer expected life time of SN that first dies by giving more weight value to weight factor w_v . In case that total life time of WSNs is more important, the bigger value is assigned to weight factor w_a rather than w_v .

5 Conclusion and Future Work

A genetic algorithmic topology control scheme for WSNs, named *GA-OTC*, is proposed to balance and minimize energy consumption. A genetic algorithm is used to search for the optimal clustering set of SNs. In addition, in order to solve a multi-objective problem, weight factors are used for two objective functions, i.e., balanced energy consumption and minimized total energy consumption. By using weight factors, *GA-OTC* can determine the objectives to optimize. Our novel scheme shows better performance on balancing and minimizing energy consumption than shortest distance based algorithm and LLC algorithm. As for future work, we consider applying another meta-heuristic such as simulated annealing and tabu search to the proposed optimized topology control scheme.

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