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A MULTI-OBJECTIVE EVOLUTIONARY ALGORITHM FOR IMPROVING ENERGY CONSUMPTION IN WIRELESS SENSOR NETWORKS

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Abstract

Energy consumption and coverage problem are two important issues in wireless sensor networks. In this paper, we are going to maintain sensing coverage in a heterogeneous wireless sensor network with an adjustable sensing range that is randomly developed, in such a way that small numbers of sensor nodes are active, and therefore a small amount of energy is consumed, and the network lifetime increases. This is a multi-objective optimization problem. We used a Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) for solving this problem.The experimental results demonstrated that MOEA/D can perform better than NSGA-II.

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Key words: deployment, sensor networks, multi-objective optimization, evolutionary algorithms, Pareto optimality

1 Indroduction

With the growth of technology, wireless sensor networks (WSNs) will have great impacts on our lives in the near future. WSNs have many applications in various fields such as battlefield surveillance, biological detection, home appliance, smart spaces, national security, surveillance, military, health care, inventory tracking and environmental monitoring [2].

A wireless sensor network is a large set of sensors that are deployed closely, and are connected together by a wireless antenna. These sensors are low-power and low-cost, and are composed of several units of sensing, processing, sending, receiving and

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storing the data [1]. For doing these tasks, especially monitoring and transmitting data that need more energy, each sensor node has been equipped with a tiny battery [3], but there are several limitations: these energy suppliers are very limited, and recharging or replacing them is so difficult [4]. Thus by improving the mechanisms that optimize energy consumption, we can prolong the lifetime of the network. Some of these mechanisms focus on scheduling the sensors to change between on and off mode, and some of them work by adjusting transmission or sensing range of the sensors [5].

Most of the recent studies have focused on scheduling sensors between on and off modes to optimize the network lifetime while coverage and network connectivity are maintained [6].

In this paper, we deal with both methods. We design a scheduling mechanism in which only some of the sensors are active, while all other sensors are in sleep mode. Also, for each sensor in the set, the goal is setting sensing range while application requirements are met.

In the networks with adjustable range sensors, these main issues should be solved: 1- The rule that decides which sensor becomes either active or sleepy. 2- If the sensor gets active, how much should its sensing range be? 3-When should nodes make these decisions [1]? If the sensing range is adjustable, the sensing range of active sensors should be dynamically adjusted so that the overall sensing objective is met. This principle can be also applied to a communication range of the sensors. It means that if the communication range is adjustable, the energy consumption can be optimized by minimizing the communication range while maintaining the connectivity and coverage [2]. Thus, in addition, energy consumption and coverage should be optimized.

The coverage concept is a measure of the quality of service (QoS) of the sensing function [2]. In wireless sensor networks, coverage means how well and for how long the sensors are able to observe the environment [8].

The coverage problems can be classified in the following categories: (1) area coverage whose aim is to cover an area, (2) point coverage where the aim is to cover a set of targets, and (3) Coverage problems that determine the maximal support path that traverses a sensor field. [3][4][5][6].
Another main parameter in wireless sensor networks is the network lifetime. It has been defined as the time during which the network gets disjoined in such a way that collecting data from a part of the network is impossible. Energy consumption is often used instead of a lifetime. Number of active sensors are also leading to a higher cost [4].
Reducing the total energy consumption to prolong the lifetime of the network with the highest ratio of coverage is the main objective of this paper. This goal is achieved by reducing the overlapped sensing area of sensor nodes.

The main objectives of the problem are: maximizing coverage ratio, minimizing the number of active sensors and maximizing network lifetime or diminishing energy consumption. This problem can be proved as an NP-complete problem. We apply an algorithm called MOEA/D to solving multi-objective optimization of coverage problem in wireless sensor networks, and compare it with the previous works.

The rest of the paper is organized as follows. Section 2 gives a brief summary of the related works. Section 3 describes the problem and the formulation of the coverage in sensor networks. Section 4 describes MOEA/D algorithm. Section 5 explains our approach to solving this problem. Section6 illustrates our simulation results as compared to the improved NSGA-II. Finally, section 7 concludes the paper and proposes future directions.

2 Related works

Aung [1] provides a formulation of the lifetime maximization problem with a sensor network with adjustable sensing ranges. Cardei et al. [5] proposed scheduling models for the target coverage problems of the wireless sensor networks with an adjustable sensing range. They proposed efficient heuristics sing integer programming formulation and greedy approaches. Wu and Yang [7] proposed two other node scheduling models with several levels of adjustable sensing ranges, and compared with model I that is a uniform sensing range model. Model II covers the area with non-overlapping large disks in a way that each disk "touches" six disks. The area that is enclosed by three adjacent disks is not covered. Then, it covers the area with a medium disk that is three crossings on the circumference of the medium disk. Model III covers the area with non-overlapping large disks in a way that each disk "touches" six disks. The area which is enclosed by three adjacent disks is uncovered. It embeds such a small disk in the area that it "touches" all three large disks. Three new uncovered areas are generated which are covered by three medium disks. They concluded that Model II can achieve better coverage ratio than Model I and Model III. Zalyubovskiy et al. [3] considered two types of sensor covers: model A and model B. In model A, the centers of three neighboring disks of equal radius are placed at the vertices of an equilateral triangle.

In model B, the centers of four neighboring disks of equal radius are at the vertices of a square. For each type of cover, they considered three models: A-1, A-2, and A-3, and B-1, B-2, and B-3. Newly introduced models A-3 and B-3 brought about a significant improvement in coverage efficiency. Jia et al. proposed a coverage control scheme based on elitist non-dominated sorting genetic algorithm (NSGA-II) in a heterogeneous sensor network for maintaining sensing coverage by keeping a small number of active sensor nodes and a small amount of energy consumption [9]. In this paper, we propose a MOEA/D-based approach in wireless sensor network in order to maximize coverage rate; we minimize energy consumption as well as a number of active sensors , and we compare the results with Jia's proposed algorithm.

Some papers have illustrated that MOEA/D outperforms NSGA-II. In [10], the performance of MOEA/D and NSGA-II of the multi-objective travelling salesman problem was compared (any comparison should include two elements; one is missing here). Konstantinidis et al. [11] compared these two algorithms on multi-objective Deployment and Power Assignment Problem (DPAP). In [12], the experimental results indicated that MOEA/D could significantly outperform NSGA-II on the test instances that could be used for studying the ability of MOEAs in dealing with complicated PS shapes. Zhang et al. [13] have worked on multi-objective knapsack problems and continuous multi-objective problems. The analysis has shown that MOEA/D has lower computational complexity than NSGA-II.

3 Problem definition

We assumed that N heterogeneous sensors $n_1, n_2, \ldots, n_N$ are randomly deployed to cover the whole target area at what is digitized into $m \times n$ pixels, and each pixel size is equal to 1. All nodes in a sensor network have circular sensing regions. However, this assumption may not be accurate in real world networks [14]. Each sensor n_i is centered at its coordinates (x_i, y_i) with radius r_i, which is equipped with initial energy E and energy consumption e_i, and it has the capability to adjust its sensing range. So sensing radius set is: $r_1, r_2, \ldots, r_N$ where $r_{min} < r_i < r_{max}$, corresponding to the energy consumptions of $e_1, e_2, \ldots, e_N$. The aim is finding a subset $N' \subseteq N$, in a way that (1) the coverage rate $R_{area}(N')$ is maximized, (2) the financial cost $|N'|$ (the number of sensors in the subset (N') is minimized, (3) the coverage consumption (realized by adjusting each sensor's sensing radius) is minimized, and (4) each sensor appearing in the set consumes the utmost E energy. Subset N' is named as the optimal sensor set of the target area. A random variable, c_i, is introduced to describe the event that sensor n_i covers a pixel (x, y). Then, the probability of event c_i denoted as $P(c_i)$, is equal to the coverage probability $P_{cov}(x, y, n_i)$. This may degenerate to a two-valued function,

$$P(c_i) = P_{cov}(x, y, n_i) = \begin{cases} 1, & \text{if } (x - x_i)^2 + (y - y_i)^2 \leq {r_i}^2 \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

A pixel (x, y) is covered by a sensor n_i if its distance to the center (x_i, y_i) of the circle is not larger than the radius r_i. If we assume that any random event c_i is independent from the others, c_i and c_j are unrelated,$i, j \in [1, N]$ and $i \neq j$. Then the following two relationships can be concluded:

$$P\{\bar{c_i}\} = 1 - P\{c_i\} = 1 - P_{cov}(x, y, n_i) \tag{2}$$

$$P\{c_i \cup c_j\} = 1 - P\{\bar{c_i} \cap \bar{c_j}\} = 1 - P\{\bar{c_i}\}.P\{\bar{c_j}\} \tag{3}$$

Finally, we define the coverage rate of the sensor set $R_{area}(C)$ as the proportion of the monitoring area $A_{area}(C)$ to the total area A_s.

$$R_{area}(C) = \frac{A_{area}(C)}{A_s} = \sum_{x=1}^{m} \sum_{y=1}^{n} \frac{P_{cov}(x, y, C)}{m \times n} \tag{4}$$

And the total energy consumption is:

$$E_{total} = u \tag{5}$$

The energy consumption per area is shown as:

$$\frac{E_{total}}{A_{area}} = u.\sum_{i=1}^{N} \frac{{r_i}^2}{A_{area}} \tag{6}$$

So, the objects are maximizing coverage rate $R_{area}(N') = A_{area}(N')/A_s$ and minimizing the financial cost of the sensor set $N' : |N'|/|N|$ and energy consumption of the sensor set N' [9].

$$\frac{E_{total}}{A_{area}} = \sum_{i=1}^{n} \frac{{r_i}^2}{A_{area}} \tag{7}$$

4 Multi-Objective Evolutionary Algorithm based on Decomposition

MOEA/D algorithm transforms the multi objective problem into scalar optimization sub problems. These sub-problems are solved by evolutionary methods. In the evolutionary progress, the population is generated out of the best solution in each generation. In MOEA/D each sub-problem uses the information of its neighboring sub-problems for optimization.

The neighborhood relation among these sub-problems is the distance between their aggregation coefficient vectors. The optimal solutions of two neighboring sub-problems are very close. MOEA/D general framework is as follows [13].

We assume that the nodes are randomly and statically deployed so that each node knows its own location. Since the transmission range is at least twice the sensing range, it is necessary and sufficient to ensure that coverage implies connectivity [14], thus the transmission range of sensor nodes is assumed to be at least twice the sensing range.

5 Our approach

We assume that S sensor nodes are randomly deployed in an $M \times N$ area.The location of each node is also known, and the lower bound and upper bound for each sensor are given. The aim is adjusting sensing radius and assigning on or off for each sensor so that with the minimum number of active nodes, energy consumption and area coverage be optimized. We have applied MOEA/D algorithm for this purpose.

Like [9], we represent a solution by a bit-string as shown in Figure 1. The sensing radius is encoded as a binary form and the last bit is used to show the status of the sensor node. 1 is used for active sensors and 0 for inactive sensors [9].

MOEA/D also needs to decompose a multi objective problem into a set of sub-problems. There are different decomposition methods, but in this paper, the Tchebycheff approach is used, as follows. This problem is decomposed into m scalar optimization sub-problems considering three objectives. The ith scalar optimization sub-problem and the objective function of the jth sub-problem can be defined as:

Algorithm 1 MOEA/D framework [13]

A population of N points $x^1, \ldots, x^N \in \Omega$ where x^i is the current solution to the ith subproblem;
$FV^1, \ldots, FV^N$ where FV^i is the F-value of x^i , i.e. $FV^i = F(x^i)$,for each $i = 1, \ldots, N$;
$Z = \{z_1, \ldots, z_m\}^T$ where z_i is the best value found so far for objective f_i ;
an external population (EP), which is used to store non dominated solutions found during the search.
Input:
MOP ;
A stopping criterion;
The number of the sub-problems considered in MOEA/D;
A uniform spread of weight vectors: $\lambda^1, \ldots, \lambda^N$;
The number of the weight vectors in the neighborhood of each weight vector.
Output: EP.
Step 1) Initialization:
Step 1.1) Set $EP = \phi$
Step 1.2) Compute the Euclidean distances between any two weight vectors, and then work out the T closest weight vectors to each weight vector. For each $i = 1, \ldots, N$, set $B(i) = i_1, \ldots, i_T$, where $\lambda^(i_1), \ldots, \lambda^(i_T)$ are the T closest weight vectors to λ^i.
Step 1.3) Generate an initial population $x^1, \ldots, x^N$ randomly or by a problem-specific
method. Set $FV^i = F(x^i)$.
Step 1.4) Initialize $z = (z_1, \ldots, z_m)^T$ by a problem-specific method.
Step 2) Update:
For$i = 1, \ldots, N$ do

Step 2.1) Reproduction: Randomly selects two k, l indexes from $B(i)$, and then generate a new solution y from x^k and x^l by using genetic operators.
Step 2.2) Improvement: Apply a problem-specific repair/improvement heuristic on y to produce y'.
Step 2.3) Update of z: For each $j = 1, \ldots, m$, if $z_j < f_j(y')$, then set $z_j = f_j(y')$.
Step 2.4) Update of Neighboring Solutions: For each index $j \in B(j)$, if $g^{te}(\lambda'|\lambda^i, z) \leq g^{te}(x^j|\lambda^i, z)$, then set $x^j = y$' and $FV^j = F(y')$.
Step 2.5) Update of EP:
Remove from EP all the vectors dominated by $F(y')$.
Add $F(y')$ to EP if no vectors EP in dominate $F(y')$.
Step 3) Stopping Criteria: If stopping criteria is satisfied, then stop and output EP. Otherwise, go to Step 2.

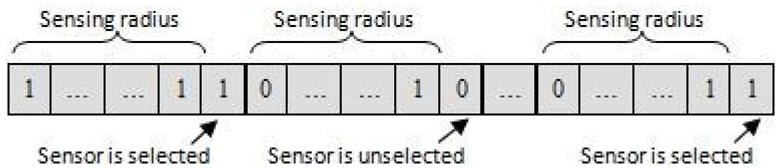

Figure 1: Problem representation [9]

Maximaized $g_i(X|\lambda_i, z^*) = Max((\lambda_i^j.R_{area} - z_i^*), (\lambda_i^j(1 - \frac{|N'|}{|N|}) - z_i^*), (\lambda_i^j(-\frac{E_{total}}{A_{area}}) - z_i^*))$. Where $1 \leq i \leq 3$ and $\lambda^j = (\lambda_1^j, \lambda_2^j, \lambda_3^j)^T$ is the set of even spread weight vectors and z^* is the reference point [6].

Step1 of MOEA/D algorithm is initialized in which we used a uniform random method to generate m solutions for the initial internal population, which contains N sensor locations (x_i, y_i) and their sensing radius r_i which both could be asleep or active.

In step 2-1, the genetic algorithm operators are activated to generate new solutions. The first genetic operator is selection operator that determines which individual actually influences the production of the next generation. [9] In this paper, we used tournament selection operator. The other operator is the crossover operator that takes a certain number of parents, and creates a certain number of children by recombining the parents [15]. We have used uniform crossover with the probability 0.2. The last operator is mutation operator the aim of which is generating new solutions within the search space by the variation of the existing ones. [15] Mutation is intended to cause only small changes in the children [16]. It works by randomly complementing some genes.

In step2-2, the repair heuristic operator increases the sensor′s individual utilization. It produces solution Z, which is used for updating the populations
İn step 2-3, the populations are updated for each solution Z_i.

In step 2-4, considering all the neighbors of the ith sub-problem, it replaces x^j with y' if y' performs better than x^j with regard to the jth sub-problem [6].

In step 3, termination criterion is checked to decide whether the search should stop or continue [11] so that our algorithm will terminate after a certain number of generations.

For measuring the coverage, we divided the area into $M \times N$ pixels. A pixel is considered as covered if it is covered by at least one sensor, and coverage is defined as the ratio of the number of pixels that are covered to the total number of pixels. Algorithm 2 finds the covered pixels and their attribute 1. This algorithm can decrease the complexity of finding covered pixels. This method has a time complexity of $O(S.Radius^2)$, as compared to previous method′s time complexity of $O(S.M.N)$. The running time of our method can be even more improved by using an adaptation of the Bresenham′s algorithm for circle. The theoretical time complexity of the algorithm remains the same $O(SRadius^2)$, but the real running time is decreased by up to $100.(1 - \pi.Radius^2/4.Radius^2)\% \approx 21.5\%$.

Algorithm 2 Finding covered points

M: Length of area
N: Width of area
$A[1:M, 1:N] = 0$
For each sensor S_i*:*
  For $x = X_i - Radius_i : X_i + Radius_i$
    For $y = Y_i - Radius_i : Y_i + Radius_i$
      if $x^2 + y^2 \leq Radius_i^2$ *then*
        $A[x, y] = 1$
      End if
    End for
  End for
End for

6 Simulation results

We randomly deployed 100 to 1000 sensor nodes in 50×50 target area. With the interval variation 1, the lower and upper bound for sensor radii were given as $r_i \in [8, 15]$. Figure 2 and Figure 3, respectively, compare energy consumption per area and active nodes number between improved NSGA-II method and our approach with each other by using MOEA/D algorithm. As shown in these figures, MOEA/D needed lower energy consumption and lower nodes to operate in the active mode as compared to the improved NSGA-II algorithm, but it achieves almost the same coverage. In addition MOEA/D has lower computational complexity at each generation than NSGA-II [13]. Beyond all MOEA/D will converge faster to the optimal solution.

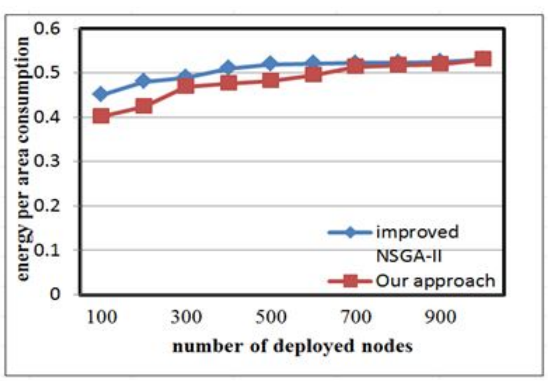

Figure 2: Energy consumption per area Vs. node density

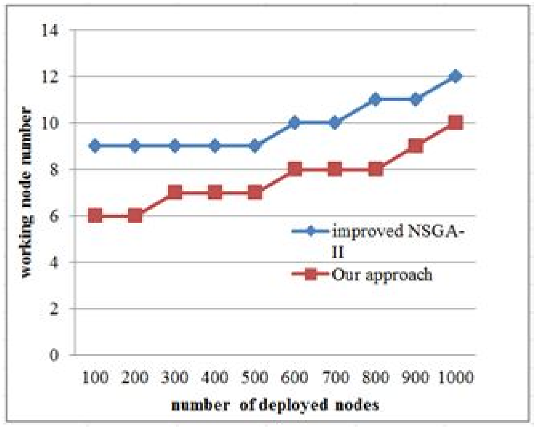

Figure 3: Working nodes Vs. node density

7 Conclusion and future directions

In this paper, we used a multi-objective evolutionary algorithm based on decomposition (MOEA/D) for improving coverage and energy consumption in wireless sensor networks with an adjustable sensing range to achieve longer lifetime and better performance. We compared this method with recent works by improving NSGA-II. Simulation results show that MOEA/D has better performance and lower cost. Furthermore, it can converge to the optimal solution sooner, and MOEA/D has lower computational complexity. Our future work will deal with combining genetic operators of this algorithm with fuzzy logic and will study its efficiency in regard to this problem.

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