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A genetic algorithm for target coverage problem in directional sensor networks

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Abstract

Unlike traditional sensors with full-angle sensing range, directional sensors can only monitor for limited sensing ranges and angles due to technical limitations or cost considerations. The directional sensor network is composed of a number of directional sensor nodes. Therefore, it is possible that when directional sensors are randomly deployed in the field, some interested targets cannot be sensed even if these targets are located within the sensing range of the directional sensors. we study the target coverage problem in directional sensor networks with rotatable sensors. A rotatable sensor in a directional sensor network is a sensor whose sensing orientaion can be rotated to any particular direction. The target coverage problem is to achieve the higher coverage rate by rotating the sensor orentation while minimizing the active sensors after deployment. In this paper, we first present a greedy algorithm to solve the target coverage problem by scheduling each sensor to appropriate direction. This greedy scheme is used as a baseline for the performance comparison. We then propose a genetic algorithm-based target coverage scheme that can find the better coverage rate while minimizing the active sensors to prolong the network lifetime by evolutionary global search technique. Simulation results showed that the genetic algorithm-based scheme outperforms than the greedy algorithm in terms of maxmizing the coverage rate and minimizing the active sensors.

Key words: Directional sensor networks, target coverage problem, genetic algorithms

Introduction

Due to the improvement of technology in the past years, the wireless sensor networks (WSN) has been widely used in the sustainable development and application on monitoring and tracking [1-5]. The sensing coverage problem is a fundamental problem and is usually related to the efficiency of sensors in performing sensing tasks in the deployed space in applications. Therefore, the sensing coverage problem has been studied by many researchers. Most of the past works are based on the sensors which have omni-directional (360°) effective sensing range. In many real applications, sensors are limited to some directions and specific sensing angle, such as infrared sensors [5], video sensors [6], and ultrasonic sensors [7]. Such sensors are called the directional sensors. As a result, research results on omni-directional sensor networks could not be applied directly in directional sensor networks (DSN) which is composed of many directional sensors. Therefore, there still has many challenge problems in DSN.

One of the challenge problems in DSN is the target coverage problem. In target coverage problem, the aim is to cover a set of interested targets within the sensing field. Therefore, a directional sensor can rotate its sensing direction to any direction for covering the targets. However, the deployed sensors are powered by battery and can only be activated for a limited period of time. This means that energy consumption is very crucial for prolonging the network lifespan in DSN. Therefore, the target coverage problem is to maximize the number of covered targets while minimizing the number of working sensors in order to maximize the network lifetime.

In this paper, we proposed a genetic based algorithm for the target coverage problem in DSN. There are two objectives for the target coverage problem: maximizing the number of covered targets and minimizing the number of working sensors. These objectives can be achieved using a genetic algorithm (GA) that runs reasonable crossover and mutation operations to ensure compliance with the topology of actual sensor networks and the demand for the sensing direction rotation among nodes, in order to solve the target coverage problem.

The remainder of this paper is organized as follows: Section 2 introduces previous works related to the coverage problem in DSN. In Section 3, we formally define the target coverage problem with rotatable directional sensor. In Section 4, our proposed genetic algorithm-based scheme is presented. Section 5 presents some simulation results and evaluates the performance of proposed algorithms. Section 6 presents conclusions and briefly describes our future work.

Related Work

Target coverage in omni-directional sensor networks is an important issue that have been widely discussed. When a group of targets are scattered across a network, the authors in [8] assumed that each sensor can only cover one target at a time, and established a coverage timetable for maximizing the network lifetime. The authors in [9-10] proposed methods to organize all sensors into different groups and then allowing these groups to be successively activated to extend the network lifetime.

In recent years, the coverage problem in DSN has attracted the attention of many researchers. Ai and Abouzeid [11] proposed a model of sensor network with orientation adjustable sensor node. They define the Maximum Coverage with Minimum Sensors (MCMS) problem with the goal of maximizing the coverage rate while minimizing the number of active sensors. They also presented the Centralized Greedy Algorithm (CGA) and Distributed Greedy Algorithm (DGA) for the MCMS problem. Cai et al. [12] defined the Directional Cover Set problem (DCS) of finding a cover set of targets and proved that the DCS problem is NP-Complete. Liang and Chen [13] defined Maximum Coverage with Rotatable Angles

(MCRA) problem for directional sensors with rotatable angles in which the number of targets to be covered is maximized while the angles to be rotated is minimized. They presented two centralized greedy algorithms, namely the Maximal Rotatable Angles (MRA) scheme and the Maximum Coverage First (MCF) scheme, to rotate the working direction of sensors for the MCRA problem. Both of their proposed greedy methods are based on the weights of working direction of sensors. Accordingly, the sensors could rotate their working directions to cover more targets. In [14], the authors presented a greedy method based on constructing the sensing directions according to the targets within the sensors to improve the coverage rate obtained by [13]. In this paper, we construct a genetic algorithm to improve the result of greedy algorithm to achieve better target coverage rate.

Rotatable Sensors for Target Coverage Problem

In this section, the sensing model of the rotatable sensors in DSN and the definition of the target coverage problem with rotatable sensors are described as follows.

A. Sensing Model

The sensing model of a directional sensor s can be described as follows and shown as in Fig. 1: Suppose that a sensor s is located in the plane with location (x, y). Let r denote its sensing radius, D be the orientation indicating the sensing direction of sensor s, and α denote the offset angle of the field of view on both side of D. The field of view of sensor s is enclosed by two radii between D-α and D+α. In addition, a target t can be covered by a sensor s if its location is within the sector area of sensor s.

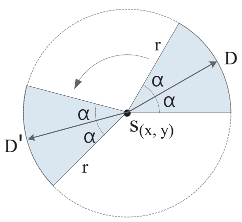

Fig. 1. The directional sensing model of rotatable sensors.

B. Problem Definition

It should be noticed that a target in DSN cannot be covered by a sensor even if the target is located within the sensing radius of the sensor. For covering the target, the sensor needs to rotate its sensing direction. Such situation can be illustrated in the example shown in Fig. 2. In Fig. 2(a), there are 3 targets, namely t_1, t_2 and t_3, located within the sensing range of deployed sensor s with sensing orientation D. It can be seen that targets t_1 and t_2 are covered by the sensor. However, target t_3 can also be covered if sensor s rotates its sensing orientation clockwise to D'.

In this paper, our aim is to find the appropriate sensing direction of each sensor so that the number of targets can be covered is maximized. Meanwhile, for the sake of energy saving, the number of activated sensor is minimized. Therefore, our goal is to maximize the target coverage rate while minimizing the total number of active sensors.

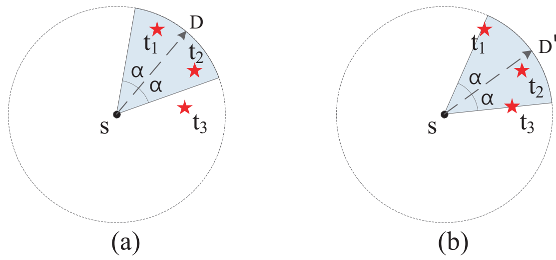

Fig. 2. An example for a directional sensor to cover more targets by rotating its sensing direction.

Proposed Genetic Algorithm

We develop a genetic algorithm to find the optimal or near-optimal solutions for the aforementioned target coverage problem in DSN. Following sections describe the fundamental parts of our proposed genetic algorithm.

A. Problem Representation

Finding appropriate working direction for each sensor is critically important to maximizing the target coverage. Given a set of m targets $T = \{t_1, t_2, \ldots, t_m\}$, a set of directional sensor nodes $S = \{s_1, s_2, \ldots, s_n\}$, and each sensor s_i has p_i possible sensing directions, then a possible sensor sensing direction arrangement or chromosome can be represented as follows:

$$(d_1, d_2, ..., d_n)$$

where d_i represents the sensing direction sensor s_i, and $0 \le d_i \le p_i$. In this representation, when $d_i = 0$, it means that sensor s_i is inactive to conserve energy.

B. GA Operators

In genetic algorithms, the selection process is intended to provide and improve the quality of population, while crossover and mutation provide the ability to generate new population. Therefore, the effectiveness of a genetic algorithm depends not only the ability of improving the quality of population but also the ability of generating new population.

- **Crossover**: The crossover operation will first select two individuals and then produce two new individuals by exchanging parts of their chromogene according to probability specified by the crossover rate. In this paper, we use two-point crossover. This means that two selected individuals exchange portions between the boundaries a segment indicated by two points. Following shows an example of crossover operation:

  $$Indv_1 : (1, 2, 1, 3, 0, 2, 3, 2, 2)$$

  $$Indv_2 : (0, 2, 1, 2, 2, 1, 3, 2, 1)$$

  After crossover on the second segment, two offspring are created as below:

  $$Child_1 : (1, 2, 1, 2, 2, 1, 3, 2, 2)$$

  $$Child_2 : (0, 2, 1, 3, 0, 2, 3, 2, 1)$$

- **Mutation**: In an individual, the mutation operator is applied to each sensor with a probability specified by the *mutation rate*. When applied, we randomly choose one sensor to change its sensing direction. The following shows an example of mutation:

mutation point

↓

Indv : (1, 2, 1, 3, 0, 4, 1, 0, 3)

↓ change sensing direction

Indv : (1, 2, 1, 3, 0, 2, 1, 0, 3)

C. Selection

The purpose of selection process is to choose the candidate individuals based on their fitness from the population in the current generation. In our proposed genetic algorithm, we use the roulette wheel method to implement the selection process. By using a biased roulette wheel, we assign a slot to each individual, and the slot size is proportional to the individual's fitness value. As a result, individuals with higher fitness values will be more likely to be selected as individuals of population in the next generation.

D. Fitness Evaluation

The selection process chooses the candidate individuals based on their fitness from the population in the current generation. In our proposed genetic algorithm, we use the roulette wheel method to implement the selection process. By using a biased roulette wheel, we assign a slot to each individual, and the slot size is proportional to the individual's fitness value. As a result, individuals with higher fitness values will be more likely to be selected as individuals of population in the next generation.

There are two main factors needed to be optimized in our genetic algorithm, namely the total target coverage rate and the farthest moving distance among all sensors. Therefore, we define the following equation which consists of two components to evaluate the fitness of each individual:

$$F = w \times R + (1 - w) \times \frac{n - k}{n}$$

where R is the target coverage rate, k is the number of active sensors, and w is a predefined weight, $0 \leq w \leq 1$. The target coverage rate is the percentage of targets covered by sensors in network. The proposed genetic algorithm aims to maximize the fitness value for finding a good solution.

Simulation Results

To evaluate the performance, we implemented the proposed genetic algorithm compared to the result obtained by the greedy solution proposed by [14] and also conducted a set of simulation experiments. All experiments were performed by a program in C# on .NET platform. We repeatedly performed each experiment 20 times, and averaged the recorded data into final results. We assume that the size of interested area is a $100m \times 100m$ rectangular area and the sensing range of each sensor is $10m$ with the angle of field of view 60°. Table 1 shows the parameter settings in our simulations.

Fig. 3 shows the impact of the number of sensors to the target coverage of our proposed genetic algorithm when $w = 1.0$, and $Ic = 100$. The range of the number of sensors is from 50 to 200 with each increase of 25 sensors. In this experiment, we only focus on the objective function of maximizing the target coverage rate of all sensors.

TABLE I
PARAMETER SETTING IN SIMULATIONS

Parameter	Value	Meaning
n	200	Number of targets
m	50, 75, ..., 200	Number of sensors
P	100	Population size
p_c	0.8	Probability of crossover
p_m	0.01	Probability of mutation
w	0.5, 1	Weight of fitness function
Ic	100	Iteration count

In Fig. 3, we can see that our proposed genetic algorithm can obtain the better coverage rate than the previously proposed greedy algorithm.

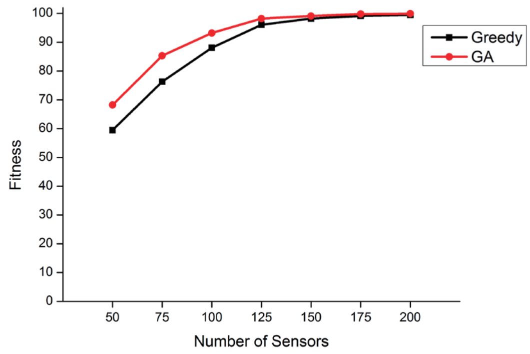

Fig. 3. Fitness of GA when $w = 1.0$ and $Ic = 100$.

Fig. 4 shows the evaluation process of our genetic algorithm. In Fig. 4, the progress of average fitness value for 20 runs is plotted when $w = 1.0$, and $Ic = 200$. In this case, the fitness value indicates the target coverage rate. Furthermore, a black line represents the average fitness when 50 sensors are deployed for covering 200 targets. The red line represents the average fitness when 100 sensors are deployed. From Fig. 4, it can be seen that two fitness curves grow higher as the generation increases. As a result, our proposed genetic algorithm can sufficiently find the global optimal solution for the target coverage problem.

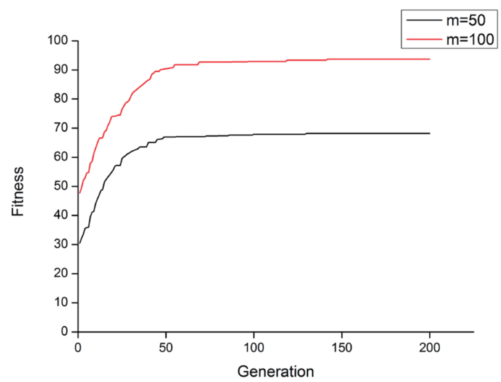

Fig. 4. Evolition process of average fitness for 20 runs of our genetic algorithm.

Fig. 5 shows the effect of the number of evolutionary generation on fitness function in the proposed genetic algorithm when $w = 0.5$, and $Ic = 100$. In this experiment, we not only need to maximize the total target coverage rate but also focus on the objective function of minimizing the number of active sensors for conserving energy. In Fig. 5, the proposed genetic algorithm can only obtain a near-optimal solution with 5.91% error rate compared to the optimal solution after 100 iterations. However, the genetic algorithm can quickly approach the near-optimal solution. In our experiments, the genetic algorithm can obtain the near-optimal solution in less one second while the optimal solution takes about 300 hours by brute-force manner.

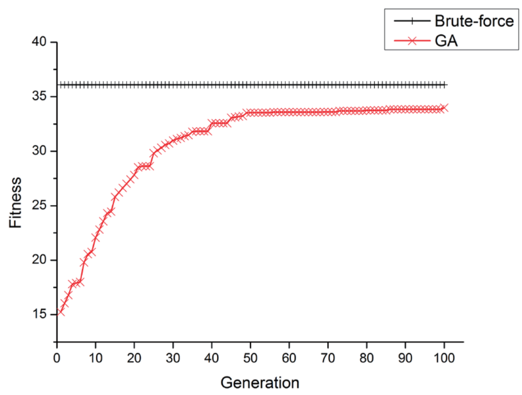

Fig. 5. Fitness of GA when $m = 50$, $w = 0.5$ and $Ic = 100$.

Furthermore, we continue the previous experiment by extending the iteration count from 100 to 500 to see the performance of proposed genetic algorithm. Fig. 6 shows the experimental result of our proposed genetic algorithm when $m = 50$, $w = 0.5$, and $Ic = 500$. In Fig. 6, we can see that, as the number of iteration increases, the fitness is getting better and better. After 500 generations, the genetic algorithm finds the optimal solution. In fact, the optimal solution can be obtained after around 495 generations. The computing time takes less 3 seconds for running 500 generations. Therefore, our proposed genetic algorithm is effective for finding the optimal or near-optimal solutions for the object coverage problem.

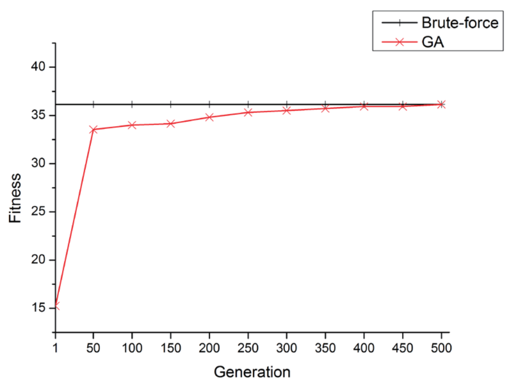

Fig. 6. Fitness of GA when $m = 50$, $w = 0.5$ and $Ic = 500$.

Conclusions

In this paper, we consider the target coverage problem in a directional sensor network. We are asked to find a better coverage for the directional sensors deployed on the target area while minimizing the total number of active sensors in order to save energy. We therefore propose a GA-based method to find the optimal or near-optimal solution for the target coverage problem. Simulation results show that our approach is an efficient and effective method for solving this problem compared to the traditional greedy methods. First, it is able to quickly find the optimal or near-optimal solutions. Second, our proposed algorithm is applicable to the situations as the number of sensors or the number of targets is getting larger.

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