COVER SET FORMATION FOR TARGET COVERAGE USING GENETIC ALGORITHM IN DIRECTIONAL SENSOR NETWORKS

Shaharuddin Salleh, Hosen Mohamadi and Wan Rohaizad Wan Ibrahim
Center for Industrial and Applied Mathematics
Department of Mathematical Sciences
Universiti Teknologi Malaysia
81310 Johor Bahru, Malaysia
{ss@utm.my, h_mohamadi1983@gmail.com, wan_rohaizad@hotmail.com}

ABSTRACT
Maximizing the network lifetime is one important factor in covering a set of targets in directional sensor networks (DSNs). The targets may take time to be located, and a good tracking management system is necessary to locate them. Target coverage problem arises due to limitation in the sensing angle and battery power of directional sensors. The problem becomes more challenging when the targets have different coverage quality requirements. In the present study, this problem is referred to as Priority-based Target Coverage (PTC) that has been proven to be an NP-complete problem. As sensors are often deployed densely, a promising solution to this problem is the use of scheduling technique through which the sensors are partitioned into several cover sets, then the cover sets are activated successively. In this paper, we propose a genetic-based scheduling algorithm to solve the problem. In order to examine the impact of different factors on the size of the resulting subset, three different experiments were performed to test the effectiveness of our algorithm. The results demonstrated that the proposed algorithm was able to contribute to solving the problem significantly.

KEY WORDS
Directional sensor networks, target coverage problem, cover set formation, genetic algorithm

1. Introduction
In recent years, Wireless Sensor Networks (WSNs) have been widely spread due to rapid advancements in wireless communication technologies and embedded systems. WSNs are employed in collecting data from harsh and remote environments and in a number of applications such as fire monitoring in forests, tsunami monitoring in deep sea, and battlefield surveillance. Due to risk and/or cost considerations in such environments and applications, sensor nodes are deployed typically in a random manner rather than accurate placement. The random deployment demands deploying more sensors than actually required, which makes the network more resistant to faults because each target can be monitored by more than one sensor. Each sensor is equipped with a limited-lifetime battery that cannot be replaced in remote or harsh environments. As a result, extending the network lifetime is one of the most important problems in designing WSNs for such environments [1, 2].

Due to densely deployment of sensors in these environments, a promising solution to this problem is organizing the sensors into several cover sets such that the set of sensors in each cover set can monitor all the targets for a given amount of time [4, 5, 6]. At any unit of time, sensors that belong to only one cover set are activated and others are switched to inactive mode. This solution that is known as scheduling technique leads to a considerable increase in network lifetime due to two reasons. First, sensors consume very less amount of energy in the inactive mode compared to the active mode, hence saving a lot of energy. Second, if the battery of a sensor oscillates frequently between active and inactive modes, the battery lasts for a longer duration [1]. This paper addresses the lifetime maximization problem in Directional Sensor Networks (DSNs) that are WSNs consisting of only directional sensors. Directional sensors (e.g., video sensors, ultrasonic sensors, and infrared sensors) can monitor only the targets located in their one angular sector [3, 4].

During recent years, some studies have been carried out to solve the target coverage problem based on scheduling technique (See [4, 7, 8, 9, 10]). Ai and Abouzeid [4] were among the pioneers who studied the target coverage problem in DSNs. They modeled a maximum coverage with the minimum sensors problem to maximize the number of covered targets with a minimum number of active sensors. In [5], the authors defined the multiple directional cover set problem and proved its NP-completeness. They proposed several heuristic algorithms to find non-disjoint cover sets each of which covers all targets. In [11], the authors proposed two algorithms for
solving target coverage problem; one based on greedy method and the other one based on genetic algorithm. In [12, 13, 14], the authors proposed several learning automata-based scheduling algorithms for solving the target coverage problem in DSNs.

Wang et al. [18] introduced the problem of priority-based target coverage (PTC) in DSNs, which aimed at choosing a minimum subset of directional sensors that was able to satisfy the prescribed priorities of all the targets. They proposed a genetic algorithm for solving this problem. Yang et al. [17] also assumed that the targets required different coverage quality requirements according to their roles in the application. In addition, they assumed the distance between the target and the sensor affected the coverage quality. They proposed a greedy-based scheduling algorithm that was able to find a sequence of feasible cover sets in order to prolong the network lifetime.

This paper proposes a scheduling algorithm based on genetic algorithm (GA) as a solution to the PTC problem. The proposed algorithm attempts to construct the cover set with minimum number of active sensor directions. To evaluate the performance of the proposed algorithm, several experiments were conducted through which the effects of different parameters on the size of constructed cover set were investigated.

This paper is organized as follows: Section 2 introduces PTC problem in DSNs. Section 3 briefly describes GA. In Section 4, a GA-based scheduling algorithm is presented for solving the problem. In Section 5, the performance of the proposed algorithm is evaluated through several experiments. Finally, Section 6 contains the conclusion and future directions.

2. Problem Definition

In this study, we investigate the following scenario. Several targets with known locations are distributed within a two-dimensional Euclidean field. Different coverage quality requirements are assigned to each target, indicating its importance. In other words, a higher value of coverage quality indicates a higher importance for the target. In this field, a number of directional sensors are randomly deployed in the vicinity of the targets in order to satisfy their coverage quality requirements. Each directional sensor has several non-overlapping directions; however, at each given time, only one of its directions can be activated (known as working direction). Each directional sensor is provided with a device that is capable of switching the direction of the sensor over a range of directions. A target is monitored by a directional sensor only if it is located within both the sensing range and working direction of the sensor. But the problem is that the quality of monitoring depends on the distance between the directional sensors and targets. That is, with an increase in the distance, the coverage quality usually decreases, and vice versa. Note that a target may require to be monitored by more than one directional sensor simultaneously in order that its coverage quality requirement could be fully satisfied. A general assumption is that the coverage quality requirement of a target that could be satisfied is equal to the sum of coverage provided by the sensor directions that cover the target. In this paper, we use the following notation:

\[ M : \text{the number of targets} \]
\[ N : \text{the number of sensors} \]
\[ W : \text{the number of directions per sensor} \]
\[ t_m : \text{the } m\text{-th target, } 1 \leq m \leq M \]
\[ s_i : \text{the } i\text{-th sensor, } 1 \leq i \leq N \]
\[ d_{ij} : \text{the } j\text{-th direction of the } i\text{-th sensor, } 1 \leq i \leq N, 1 \leq j \leq W \]
\[ T = \text{the set of targets, } t_i \text{ for } i = 1, 2, ..., M \]
\[ S = \text{the set of sensors, } s_j \text{ for } j = 1, 2, ..., N \]
\[ u(x) : \text{the coverage quality function; where } x \text{ signifies the ratio of the distance between the sensor and target to the sensing range} \]
\[ g(m) : \text{the required coverage quality of target } t_M \]

The functions \( u(x) \) and \( g(m) \) depend on the context of networks and the application requirements. These functions are defined as follow [17]:

\[ u(x) = 1 - x^2 \]

and the value of \( g(m) \) is selected between 0 and 1 randomly and uniformly.

Problem: How to find a minimum subset of sensor directions to satisfy different coverage requirements of all the targets. In [6], this problem has been proved as an NP-Hard problem even where sensors had a 360° sensing ability and the targets had the same coverage quality requirements.

Definition: A cover set consists of a subset of sensor directions by which the coverage quality requirements of all the targets can be satisfied.

Figure 1 shows a simple case of five sensors \( s_i \) for \( i = 1, 2, ..., 5 \) for detecting three targets \( r_1, r_2 \) and \( r_3 \). Two cover sets \( S_1 = \{s_1, s_2, s_3\} \) and \( S_2 = \{s_3, s_4, s_5\} \) are formed to provide an efficient coverage for the three targets. Obviously, \( S_1 \) covers \( r_1 \) and \( r_2 \) while \( S_2 \) covers \( r_1 \) and \( r_3 \). The coverage becomes very effective as \( r_1 \) is
covered by \( s_1 \) and \( s_2 \) inside \( S_1 \) while \( r_3 \) is covered by \( s_4 \) and \( s_5 \) inside \( S_2 \).

Figure 1. Two cover sets for 5 sensors and 3 targets.

3. Genetic Algorithm

There are different methods in evolutionary computation field, including genetic algorithms, evolutionary programming, evolution strategies, genetic programming, and differential evolution. GA is based on the survival of the fittest theory of Darwin and gene recombination [15]. The GA method is adaptive; thus, it can be applied to solving search and optimization problems. Obtaining an optimal solution cannot be guaranteed through merely using GAs; however, they are capable of providing appropriate solutions to various optimization problems. GA is a powerful optimization technique that does not need any inherent parallelism and gradient information in searching the design space.

GA contains a population of individuals each of which represents a potential solution to a given optimization problem. Depending on the qualification of each solution, a fitness score is assigned to that. In order to generate offspring (new solutions) by means of crossover and mutation mechanisms for the next generation, individuals are chosen from the population and recombined. GA continues until the evolutionary procedure meets a particular evolution stopping criteria.

Three main steps [16] in GA are explained briefly as follows:

Crossover: this operation produces offspring from two individuals selected from among the population. This is performed through exchanging some bits in the individuals. Therefore, the offspring inherit some features from each parent.

Mutation: this operation produces offspring through changing randomly one or some bits in an individual. Thus, offspring may gain different features from their parents. Due to creation of random diversity in the population, the mutation operation can be used as a significant element in solving the problem of premature convergence.

Selection: this operation uses some predefined rules to choose some offspring for survival. This operation keeps the size of population and, with a high probability, it puts good offspring into the next generation.

4. Our Proposed Algorithm

This paper proposes a genetic-based algorithm in order to construct a cover set with minimum number of active sensor directions during the network operation. The framework of the proposed algorithm is shown in Algorithm 1. First, the candidate solutions are encoded as chromosomes. This study uses an integer-based representation for chromosomes. Each chromosome represents a cover set and each gene of the chromosome represents the status of an individual sensor node. Each chromosome is encoded by means of an integer vector of length \( n \), where \( n \) signifies the total number of sensor nodes in the network. The value of each gene can be either 0 (indicating that sensor \( i \) is not in the cover set) or in the range of 1, 2, ..., \( W \) (indicating that sensor \( i \) with its \( j \)-th working direction is in the cover set). Then, the fitness of chromosomes is evaluated using the fitness function. In this study, fitness function is considered as the number of active sensor directions in each cover set, which satisfy the coverage quality requirements of the targets. Note that the fitness function of a cover set is better than that of other cover sets if the cover set has a lower number of active sensor directions than others.

Following the initialization of the population, the algorithm starts the evolutionary process. To this end, first, two chromosomes are selected from the population by the selection operator to serve as parents. In this study, we use the binary tournament selection method. Then, in order to produce a child chromosome from the two selected parents, the uniform crossover operator is used, which produces a child chromosome position-by-position. After the production of the child chromosome, the mutation operation is performed. For this purpose, the gene corresponding to each sensor is checked to know whether the sensor is present in the child or not. If its presence is verified, the sensor is switched to inactive mode with probability \( p_m \). Otherwise, the sensor through one of its working directions is inserted into the child with probability \( p_m \). In the proposed algorithm, elitism is considered in order to give chance to the best individual of each generation to be survived during the evolution process.
In the above algorithm, we develop a repair operator originally proposed in [1] in order to assure the feasibility of the child chromosome produced during the crossover and mutation operation. The repair operator performs two tasks: (i) transforming the child into a feasible cover set and (ii) improving the coverage rate of each cover set through eliminating the redundant sensors. The reproduction process (selection, crossover, mutation, then repair operation) continues until the offspring population is filled. Based on the “Survival of the Fittest” theory of Darwin, the fittest chromosomes from the offspring population are selected by the survivor operator. The selected chromosomes are applied to the generation of the next population. As the evolution goes on, the proposed algorithm attempts to direct the search towards the global optima. In this study, the maximum number of consecutive iterations is taken into account as stopping criterion.

Our genetic algorithm solution is summarized as follows:

```plaintext
// Our Genetic Algorithm Solution
Begin
Let $T_k$ denote the dynamic threshold at stage $k$
Let $k = 0$ denote the stage number
Repeat
  $T\_{\text{cur}} \leftarrow T$
  $C\_{\text{cur}} \leftarrow 0$
  While $T\_{\text{cur}} \neq 0$
    Select a set of chromosomes
    While coverage not satisfied do
      Perform crossovers, mutation
      Selection of new fitter chromosomes
      Add $d_{i,j}$ to correspond to $C\_{\text{cur}}$
      Update cover sets for targets covered by $d_{i,j}$
    End While
    Update the list of unsatisfied targets, $T\_{\text{cur}}$
  End While
End While
Compute the cardinality of the cover sets $C_k$
If $C_k < T_k$
  Reward the selected chromosomes
  $T_k \leftarrow C_k$
End If
  $k \leftarrow k + 1$
Until $k > K$
End
```

5. Simulation Results

This section presents several experiments conducted to examine the effects of various factors on the size of constructed cover sets. In the proposed algorithm, the probability of crossover and mutation operation was set to 0.2 and 0.05, respectively. The directional sensor network was configured as follows: $N$ sensors with uniform sensing range $r$ and sensing angle $\frac{2\pi}{3}$, and $M$ targets were distributed randomly and uniformly within a square area of size $400 \times 400m^2$. By default, the sensing range was fixed to 125(m) and the number of sensors and targets was set to 100 and 10, respectively. Each simulation scenario was executed 15 times, and the average size of the cover sets was then calculated for each scenario.

![Figure 2. Number of sensors effect on lifetime.](image)

Experiment 1. This experiment was conducted to examine the relationship between the number of sensors and the size of the constructed cover set. The number of sensors was ranged from 40 to 90 with incremental step 10. The results presented in Figure 2 show that by increasing the number of sensors, the network lifetime increases. This is because each sensor contributes in extending the network lifetime, and by working cooperatively in the form of cover sets they manage to locate the targets in a shorter time.
Experiment 2. This experiment was carried out to investigate the relationship between the number of targets and the size of constructed cover set. For this purpose, the number of targets has the range from 4 to 20 with incremental step 4. The results presented in Figure 3 show that an increase in the number of targets causes a linear increase in the size of cover set. This is natural because when the number of targets increases, more number of active sensor directions are needed to satisfy the coverage quality requirement of all the targets.

Experiment 3. This experiment examined the impact of the sensing range on the size of constructed cover sets. The sensing range was varied between 75(m) and 200(m) with incremental step 25(m). The results presented in Figure 4 indicate that an increase in the sensing range helps to construct cover set with lower number of active sensor directions. This is because once the sensing range enlarges, sensor nodes are capable of monitoring more targets and, as a result, fewer sensors are required to satisfy the coverage quality requirement of all targets.

6. Conclusion

This paper addressed the problem of target coverage in directional sensor networks in which the sensors were limited in their sensing angle and battery power, and the targets had different coverage quality requirements. To solve this problem, we proposed the genetic-based scheduling algorithm capable of constructing cover sets with minimum number of active sensors, which can satisfy coverage quality requirements of all the targets. In order to evaluate the performance of the proposed algorithm, several experiments were carried out. The results demonstrated that the proposed algorithm can contribute successfully in solving the problem.

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References


