



Learning Automata-Based Algorithm as a Solution to the Problem of Priority-Based Target Coverage in Directional Sensor Networks with Adjustable Sensing Ranges

Mohd Norsyarizad Razali^{1*}, Shaharuddin Salleh², Mohd Azzeri Md Naiem¹

¹Department of Science and Maritime Technology, Faculty of Defence Science and Technology, Universiti Pertahanan Nasional Malaysia, 57000 Kuala Lumpur, Malaysia

²Center for Industrial and Applied Mathematics, Universiti Teknologi Malaysia, 81310 Johor Bahru, Malaysia

*Corresponding author E-mail: norsyarizad@upnm.edu.my

Abstract

The limited battery power and sensing angle of directional sensors makes maximizing the network lifetime of directional sensor networks (DSNs) a challenging problem, especially when surveillance of a set of targets in a given area is involved. Sensors with multiple ranges and targets that require varied coverage further exacerbate this problem. This study refers to this problem as PTCASR—Priority-based Target Coverage with Adjustable Sensing Ranges. A promising solution to this problem is to use a scheduling technique, which involves allocation of sensors into cover sets and their successive activation thereafter. A scheduling algorithm based on learning automata is proposed in this study as a solution to this problem. To assess the performance of the proposed algorithm in extending network lifetime, several simulations were conducted.

Keywords: cover set formation; directional sensor networks; learning automata; scheduling algorithms; target coverage problem.

1. Introduction

Electronic devices, which take in, gather, and accumulate information from the environment, capable of wireless communication with other devices of this type, are called wireless sensor nodes. Wireless sensors spread abundantly in a location of interest make up what is known as WSN or wireless sensor network. It is assumed that the sensing range of these nodes is shaped like a disk [15]. However, most sensor nodes in reality have a limited sensing angle, and might only be able to sense only a fraction of a disk. This type of sensor is called directional sensors, and their corresponding sensor network is called directional sensor networks or DSNs [1]. It is crucial to extend the lifetime of sensor nodes, as they already have a limited lifetime from being powered by batteries, which, in environments that are demanding and severe, are hard to replace or recharge.

Sensor networks find it a challenge to collect varied information from the environment, a problem known as coverage, which can further be categorized as target coverage or area coverage [4]. Target coverage entails the monitoring of only crucial targets, while area coverage requires the continuous monitoring of the entire vicinity. There are three main sub-problems under the target coverage problem: i) Priority-based target coverage (PTC); ii) simple target coverage, and iii) k -coverage. The various coverage requirements by various sensor nodes, whilst maintaining the coverage requirement of the target as a priority, give rise to the problem known as PTC. Each target needs a minimum monitoring quality, which is based off the type of problem, and this is known as the coverage requirement. The first coverage problem—simple coverage—has low monitoring accuracy, and entails the monitoring of each target by at least one

sensor node. The k -coverage problem somewhat solves the simple coverage problem, as it has more reliable and accurate monitoring, in which at least a k amount of sensor nodes is set to monitor each target. This advantage is rendered void in situations involving coverage requirements that vary with the targets' need, which is true for most real-world applications. The PTC problem therefore takes into account this scenario [17]. Hence, the present study aims to simultaneously achieve maximal DSN network lifetime and solve the problem of Priority-based Target Coverage.

The past few years have seen the emergence of studies [1, 6, 7, 9, 10] aiming at solving the target coverage problem by relying on scheduling techniques. The pioneering study on PTC in DSNs is that of Ai and Abouzeid [1]. Their research tackled the problem by modeling the least amount of sensors (active), but still ensuring that the most amount of targets are covered. A number of heuristic algorithms were proposed in one research work [2] so that cover sets that are non-disjointed could be determined. The study proved the problem of NP -completeness and the problem of having more than one directional cover set to address the coverage requirement of all targets. In another study with the same objective of solving the PTC problem [3], the authors used learning automata, greedy and genetic algorithms as a basis for the scheduling algorithms as another method to solve this same problem [5, 7, 8]. DSN's problem of PTC, particularly that involving satisfying the prescribed priorities of all the targets with only a minimum subset of directional sensors, was discussed by Wang et al. [13], where they proposed a genetic algorithm to solve the problem. On the other hand, two assumptions were made in a previous study [14]: i) targets differed in terms of coverage quality requirements depending on the roles that they play in the application; ii) the distance between the sensor and the target determines coverage quality.

The study managed to prolong network lifetime using a scheduling algorithm (greedy-based) that helped choose a favorable cover set sequence. Recently, Razali *et al.* [12] proposed two algorithms for solving the problem in cases where the sensors have multiple power levels (i.e. sensors have multiple sensing ranges). The authors have also showed the comparison between the proposed algorithms and a considerable impact of multiple power levels on the network lifetime.

An algorithm based on learning automata is proposed in this paper to solve the problem known as priority-based target coverage of sensors with adjustable sensing ranges (PTCASR) that is plaguing DSNs i.e. difficulty of sensors with multiple power levels to prioritize the coverage requirements of targets. There are two simultaneous objectives of this proposed algorithm with the end objective of ensuring that the coverage quality requirements of all targets are met: i) select suitable sensing ranges for selected sensor directions to minimize energy consumption, and ii) select appropriate sensor directions. Then, the effect of varying a few parameters on network lifetime was investigated through simulations. Our findings prove that the proposed algorithm successfully solved the PTCASR problem.

This paper is divided into five sections: Section 1 gives the introduction to the study; the PTCASR problem in DSNs is introduced in Section 2; the LA-based algorithm is outlined in Section 3; Section 4 discusses the background of the scheduling algorithm in this study, which is based on learning automata; the simulation results in this study (for assessing the proposed algorithm performance) are given in Section 5; and the conclusion and future directions are included in Section 6.

2. Problem Definition

The following scenario is used in this work: a 2-D Euclidean field with several targets of known locations distributed within it, where the targets vary in coverage quality requirements, and the higher the value of coverage quality of the target, the more important the target. Next, sensors with multiple power levels are spread randomly in the field in proximity to the targets, so that the coverage quality requirements of the targets are met. There are many overlapping directions to every sensor, but each can only activate one direction at a time, i.e. each sensor only has one working direction. The direction of the sensor can be switched in many directional ranges via a device provided in the sensor. However, a target must be within the sensing range and working direction of the sensor for the sensor to be able to monitor it; hence, a higher coverage quality can be achieved if the sensor were closer to the target, and vice versa. One important observation is that multiple directional sensors might be required to ensure the coverage quality requirement of all targets is met. The assumption underlying this phenomenon is that the fulfilment of coverage quality requirement for every target is directly proportional to the total coverage that each sensor covering the target can provide. This study used the specific symbols or notations outlined in Table 1.

The problem at hand can be summarized as, "How can we arrange sensor directions into a number of cover sets, whilst still ensuring that each cover set is able to maximize network lifetime and at the same time satisfy the different coverage quality requirements of all the targets?" To answer this question, three important definitions must first be outlined:

Target: if and only if the total energy of the sensors that cover each target in the network is more or equal to the total energy of the sensors covering the target, the targets' role will become critical.

Cover set: this set satisfies the coverage quality requirements of all targets, and consists of sensor direction and sensing range subsets.

Network lifetime: the duration in which all targets' coverage quality requirements can be met [16].

Table 1: Symbols

Symbol	Description
n	Number of sensors
m	Number of targets
w	Number of directions per sensor, $w \geq 1$
a	Number of alternative power levels, $a \geq 1$
s_i	A sensor for all $i \in \{1, \dots, n\}$
t_k	A target for all $k \in \{1, \dots, m\}$
l_i	Lifetime of sensor s_i
$d_{i,j}$	i -th direction of i -th sensor
S	Set of sensors, $\{s_1, \dots, s_n\}$
T	Set of targets, $\{t_1, \dots, t_m\}$
$(d_{i,j})$	A pair defined as adjusted sensor direction, denoting level- a -activated sensor direction $d_{i,j}$
$T(d_{i,j})$	Denotes the target for the adjusted sensor direction above, $(d_{i,j})$ activated at level a , in which its coverage quality requirement has been fully or partially satisfied.
$U(x)$	Denotes the coverage quality function, i.e. ratio of target and sensor length of separation to sensing range, given by x ; $u(x) = 1 - x^2$
$g(m)$	Target t_m 's coverage quality requirement, where the random and uniform selection between 0 to 1 will make up the value of $g(m)$.

3. Learning Automata

An integral part of the learning automata is the learning automaton. This learning automaton can be defined as a unit that makes decisions adaptively. The automaton learns to choose the best or most optimum action from an action set that is finite. In this way, it will continuously improve its performance [11]. The automaton works based on a series of steps designed to enable it to interact with its environment. These steps are outlined as follows: i) given an action probability vector, the automaton will select one available action; ii) the action selected is input into the random environment; iii) the environment responds to the selected action with a reinforcement feedback based on a reinforcement signal; and iv) this feedback will update the learning automaton's action probability vector. The learning automaton will generally aim to maximize the reward given by the environment, so it will always determine the most optimum action from its given set of actions [11].

4. Proposed Algorithm

This paper proposes an algorithm based on learning automata (LA), which could solve the PTCASR problem. The algorithm helps solve the problem by providing the best sensing range and sensor directions as part of the cover set it generates. Algorithm 1 outlines the proposed algorithm's framework. This algorithm is based on several rounds of operations, where a cover set is generated every round. Each round operates in two phases. A 3-step initialization phase is the first phase, consisting of generation of LA network; definition of LA action-set; and configuration of LA vector action probability. The cover set is formed in the second phase via the LA's selection of an appropriate adjusted sensor direction subset.

There are a number of stages involved in the algorithm, each starting with a cover set formation comprising LA-selected sensor direction subsets. Then, a random environment, in this case, the DSN, will evaluate the constructed cover set—whether optimal or

not. The total energy used up by the cover sets that were constructed is calculated by the environment, which then outputs an optimality response. This response determines whether the actions selected will be penalized or rewarded. Once the minimum energy consumption is reached, the cover set construction and the action probability vector updates—both iterative processes—will be stopped.

Targets that have not had their coverage quality requirements met are kept in a list under Set T_{cur} . Meanwhile, adjusted sensor directions pre-selected to meet all target's coverage quality requirement are grouped in a list under Set C_{cur} . The condition for the formation of a cover set is that A_i (a critical passive automaton) has been selected and activated. To speed up the convergence of the algorithm, the number of actions could be reduced using the pruning rule. Therefore, A_i uses this rule to achieve two things: i) to select an action (a sensor direction that has been adjusted, which will cover the critical target) out of a number of actions available; and ii) to prune its action set. Following this, set C_{cur} will expand to include the sensor direction for the action selected, $(d_{i,j}, a)$. Then, $(d_{i,j}, a)$ will be updated in terms of coverage quality requirement. Following this process, two events will happen; either the next critical automaton will be selected or the already activated automaton will select another action depending on the coverage quality requirements having been satisfied or not. This iterative process of activating the passive automaton and selecting actions will only come to a halt once the end condition is met. This end condition is the satisfaction of coverage quality requirements of all targets.

Algorithm 1 Learning Automata-based Algorithm

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01. input: DSN
02. output: Cover set consuming only minimum energy
03. assumption:
04. Each target is assigned an automaton
05. The action set of automaton  $A_i$  is denoted by  $a_i$ 
06. begin
07. The dynamic threshold at stage  $k$  is denoted by  $T_k$ 
08. The stage number is denoted by  $k$  and initially set to zero
09. repeat
10.  $T_{cur} \leftarrow T$ 
11.  $C_{cur} \leftarrow \emptyset$ 
12. while  $T_{cur} \neq \emptyset$  do
13. A critical passive automaton is found and activated. Let it be
    denoted by  $A_i$ 
14. while (not meeting the requirement for coverage quality of
    critical targets)
do
15. Given its set of actions,  $A_i$  starts to prune them, then selects
    one of these actions (say  $(d_{i,j}, a)$ )
16.  $(d_{i,j}, a)$ , which corresponds to the selected action, is added to
 $C_{cur}$ 
17. The targets covered by the selected direction  $(d_{i,j}, a)$  under-
    goes a coverage requirement update
18. end while
19.  $T_{cur}$ , which denotes the list of unsatisfied targets, is updated
20. end while
21. All disabled actions are enabled again, to update activated au-
    tomata configuration
22. set  $C_k$ , the constructed cover set, is assessed for SumE, its
    energy consumption
23. if  $\text{SumE} \leq T_k$  then
24. The actions selected by the activated automata is rewarded
25.  $T_k \leftarrow \text{SumE}$ 
26. end if
27.  $k \leftarrow k + 1$ 
28. until (the stage number  $k$  exceeds  $K$ )
29. end algorithm

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5. Simulation

Changes in certain parameters were affected and the impact on network lifetime assessed via a few simulations, the details of which are presented in-depth in this section. The directional sensor network was configured as follows. Several targets with different coverage quality requirements were distributed randomly in an environment $500(m) \times 500(m)$ in size. The first step to fulfilling the coverage quality requirement for all targets was the scattering of some directional sensors close to the targets. The average network lifetime was obtained after each scenario was executed 30 times. As a rule, only three directions and one energy unit are allotted for each sensor; furthermore, sensing range was fixed to 150 meters, with 150 sensors, and 10 targets.

Any algorithm based on Learning Automata will be affected by learning rate. Therefore, it is important to determine accurate learning rate to ensure the algorithm outputs acceptable results in a running time that is reasonable [6, 7]. The learning rate for the LA-based algorithm in all simulations in this study was set to 0.1.

5.1. Simulation 1

What will happen to network lifetime if fewer or more sensors are used? This is the main question that is answered in Simulation 1. Power levels from 1 to 4 with an incremental step of 1 were used. One hundred to two hundred sensors were used with 25-step increments. Note that the sensing range of all sensors will be fixed when power level is equal to 1. The findings of this simulation are presented in Fig. 1, which displays a direct relationship between the two; the more sensors used, the more the network lifetime is extended. The main reason for this is that the formation of cover sets increases due to the higher number of sensors, and thus more of the targets' coverage quality requirements will be satisfied. An important observation was that network lifetime considerably increased when power level was increased from 1 to 4, denoting that multiple power levels considerably impacted network lifetime.

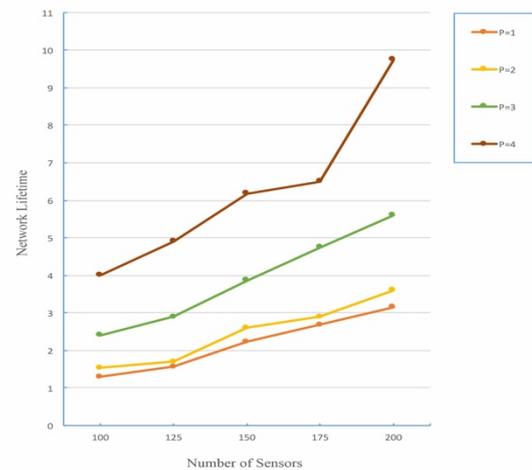


Fig. 1: Network lifetime vs. number of sensors

5.2. Simulation 2

What happens to the network lifetime if fewer or more targets are used? Simulation 2 was conducted to answer this question. Four to twenty targets were set as the number of targets, with incremental steps of 4. Fig. 2 displays an inverse relationship between the two, where the more the targets, the lesser the network lifetime. In other words, the more targets there are and hence the more requirements for coverage quality, the more sensors needed. Because of this, the network will deplete energy much faster, hence resulting in reduced network lifetime.

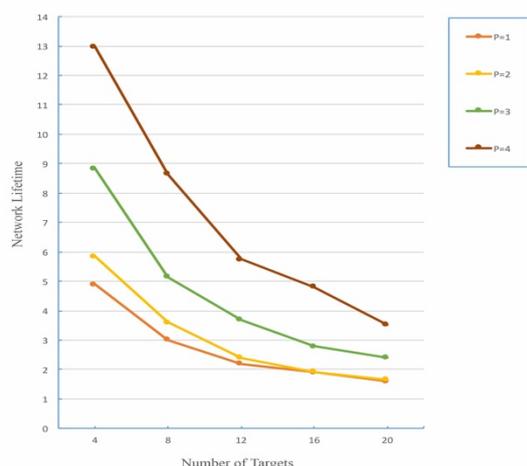


Fig. 2: Network lifetime vs. number of targets

5.3. Simulation 3

How does varying sensing range affect network lifetime? Simulation 3 is an attempt to answer this question. One hundred to two hundred meters were set as the sensing range, with incremental steps of 25 meters. Fig. 3 shows that network lifetime was increased as sensing range increased. With increased sensing range, the coverage quality of more targets can be met. In turn, the coverage of all targets could be met with fewer sensors.

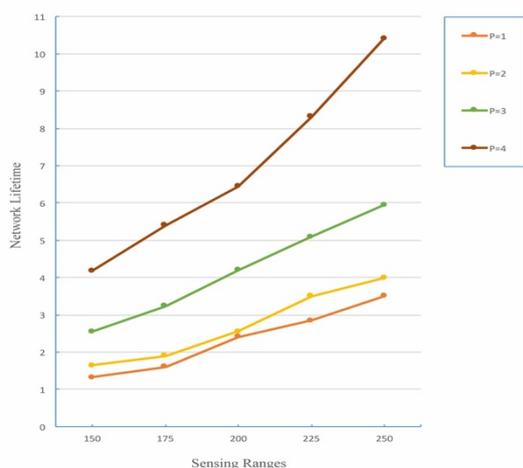


Fig. 3: Network lifetime vs. sensing range

6. Conclusion

PTCASR in DSNs was the main problem addressed in this study. This problem is characterized by the difficulty of giving priority to satisfying target coverage requirement using only a few sensors with adjustable sensing ranges. Given the limited battery power and sensing ranges of directional sensors, the main question was how to ensure network lifetime was maximized as well as satisfy the targets' varied coverage quality requirements. An algorithm based on Learning Automata, and is a scheduling algorithm, was proposed, which enables appropriate sensor directions and sensing ranges to be selected such that all targets will have their requirements for coverage quality met; thus maximizing network lifetime. Several simulations were subsequently carried out to determine whether or not the algorithm performed well in solving this issue. The findings show that the proposed algorithm contributed successfully towards solving the problem. The results also proved

that network lifetime could be greatly extended with the use of multiple sensing ranges and sensors.

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