Sensing Radius Adjustment in Wireless Sensor Networks: A Game Theoretical Approach

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Abstract—Wireless sensor networks consist of a collection of sensor nodes deployed densely and randomly to fully cover a set of targets. Due to high redundancy incurred, it is possible to both preserve energy and enhance coverage quality by first switching off some sensors and then adjusting the sensing radius of the remaining ones. In this paper, the problem of target coverage in wireless sensor networks is studied by keeping a small number of active sensor nodes and adjusting the sensing radius of nodes. We propose a new game theory-based algorithm to target coverage. Inspired by current challenges in energy-limited sensor networks, we formulate the target coverage problem with adjustable sensing range as a repeated multiplayer game in which a utility function is formulated to consider the tradeoff between energy consumption and coverage quality. To solve the formulated game and achieve the Nash equilibrium, we present a distributed payoff based learning algorithm where each sensor only remembers its utility values and actions played during the last plays. The simulation results demonstrate the performance of our proposed game-theoretic algorithm and its superiority over previous approaches in terms of increasing the coverage rate and reducing the number of active nodes.

Keywords-Sensor networks; target coverage; game theory; sensing radius adjustment; distributed learning algorithm.

I. INTRODUCTION

Sensor networks applications have been grown up and widely applied in the field of industry and our daily life. Sensor nodes collaborate to accomplish a sensing task. Providing desired target coverage in wireless sensor networks (WSNs) is a critical issue due to the limitation of energy resources in these networks [1-6]. In [6], the authors proposed a decentralized and localized density control algorithm called OGDC. Provided the density of the nodes is high in the area, OGDC selects the minimum number of sensors to cover the entire area. Sometimes the sensor nodes may not be in the optimal position, OGDC attempts to select sensing nodes as work nodes that are closest to optimal locations. The sensing radius of each sensor is the parameter that affects the energy consumption and coverage quality of WSNs. By tuning the sensing ranges of sensor nodes, the performance objectives and target coverage can be satisfied. Recently, game-theoretic approaches have been taken into consideration to solve the coverage problem in WSNs [7-10]. In [11],

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the authors proposed an algorithm based on game theory for the problem of maximizing coverage and reducing energy consumption. They have shown that the desired solution in this model is a NE strategy profile. in [12] the authors have proposed a game-theoretical complete coverage algorithm. This algorithm is used to ensure whole network coverage mainly through adjusting the covering range of nodes and controlling the network redundancy.

The game theory control method has many advantages including robustness to failures and environmental disturbances, reducing communication requirements, and improving scalability. The primary goal of game theory-based approaches is to design rules that guarantee the existence and efficiency of a pure Nash equilibrium [13]. Proper utility functions and reinforcement learning methods are designed for the coverage game of WSNs in [13, 14]. Using these algorithms, each player must have access to the utility values of its alternative actions.

This paper aims to solve the problem of optimizing the target coverage by adjusting the sensing radius of sensor nodes.

Game theory, especially potential games, is a powerful tool for designing and analyzing distributed optimization algorithms where the agents have local knowledge of the environment. We formulate this problem as a multiplayer repeated game in which each sensor as a player tries to maximize its utility function. The utility function is designed to capture the tradeoff between the worth of the covered area and energy consumption due to sensing. We show that the formulated game is a potential game, and so it has at least one Nash equilibrium. Although it is considered a non-cooperative game, where the players independently follow their objectives, their action indirectly leads to pure Nash equilibrium (NE), which is the desired global result for the optimization problem. In this game, the nodes autonomously decide on their suitable status (on/off and sensing radius adjustment). These decisions are solely based on the information received from neighbors and the results obtained from the latest actions taken by each node that is accessible in the unknown environments without any centralized control. The payoff-based learning algorithm is proposed to solve the proposed game. This algorithm employs a diminishing and fixed exploration rate and allows for the convergence in probability to the set of Nash equilibria. The contribution of this paper is to design a game for the problem of sensing radius adjustment and propose a new distributed learning algorithm to solve it.

The main contributions of this paper include:

• We then prove that the proposed game is an exact potential game and its potential function equals the objective of coverage of all targets with minimum energy consumption and fewest sensors possible to maximize the lifetime of the network.

• We propose a distributed synchronous payoff-based learning algorithm that converges to pure Nash equilibrium. The performance of the proposed algorithm is compared to OGDC algorithm in the literature through comprehensive simulations. The obtained results show that our algorithm has high energy efficiency.

The paper is organized as follows: Section II reviews some of the recent research regarding sensor coverage. In section III we introduce some preliminary game theory knowledge. The proposed algorithm is presented in section IV. In section V simulation results are presented and finally we conclude the paper in section V.

II. RELATED WORK

In this section, we briefly review the research work on coverage in wireless sensor networks. The coverage problem is usually divided into three categories: area coverage, point coverage, and barrier coverage [15-17]. The purpose of area coverage is to cover the whole area. Next, point coverage is the coverage of Points of Interest (PoI). Finally, the barrier coverage guarantees that every movement that crosses a barrier of sensors will be detected.

Habibi et al. [18] proposed a distributed Voroni-based strategy to maximize the sensing coverage in a mobile sensor network. In this algorithm, each sensor moves through a gradient-based nonlinear optimization approach and places inside its Voroni cell.

For the first time, Ai et al. [19] studied the problem of covering targets with directional sensors. They formulated the problem as maximum coverage with a minimum number of sensors and proved that it is NP-complete. Therefore, several greedy heuristic methods are presented to solve the problem. Here, the main idea is the selection of sensing sectors, which cover the maximum number of targets.

Yu et al. [17] addressed the problem of K-coverage in wireless sensor networks with both centralized and distributed protocols. Protocols introduced a new concept of the Coverage Contribution Area (CCA). Based on this concept, a lower sensor spatial density was provided. Besides, the protocols considered the remaining energies of the sensors. Therefore, the proposed protocols prolonged the network's lifetime.

Coverage Configuration Protocol (CCP) [20] is a distributed message-based algorithm that provides the required coverage with the condition of $R \geq 2r$. In CCP, a sensor node, depending on information about its neighbors, can be asleep state for energy storage, a listening state for collecting neighbor messages and deciding its new state, or an active state for sensing the environment.

In [21], a Probabilistic coverage preserving protocol (CPP) is designed to achieve energy efficiency and to ensure a certain coverage rate. The purpose of the
proposed protocol is to select the minimum number of probabilistic sensors to reduce energy consumption.

A graph model named Cover Adjacent Net (CA-Net) was proposed by Weng et al. [16] to simplify the problem of k-barrier coverage while reducing the complexity of computation. Based on the developed CA-Net, two distributed algorithms, called BCA and TOBA, were presented for energy balance and maximum network lifetime.

Mostafaei et al. [15] Proposed a distributed boundary surveillance (DBS) algorithm to cover the boundary and reduce the energy consumption of sensors. DBS selects the minimum number of sensors to increase the network lifetime using learning automata.

In [22] coverage of an unknown environment was investigated by robots. The state-based potential game was designed to control the robots’ actions. The reward of sensing the areas and the penalty of energy consumption due to the sensors’ movement were considered in the utility function. Agents updated their action profile using the Binary Log-Linear Learning (BLLL) in which the agents must know an estimate of the outcome of their future actions. Hence, an estimation algorithm was used to assist the agents in predicting the probability of targets in unknown areas.

An improved EM algorithm was introduced to estimate the number of targets and other probability distribution parameters.

III. BACKGROUND IN GAME THEORY

In this section, we consider a brief review of the concepts in game theory. More information about game theory and learning in game theory is mentioned in [23, 24].

A strategic game \( G := \{N, A, U\} \) has three components:

1. The finite set of N players where \( N := \{1,\ldots , n\} \).
2. An action set \( A = A_1 \times \ldots \times A_n \) where \( A_i \) is the finite action set of player \( i \).
3. The set of utility functions \( U \), where the action profile \( U_j : A \rightarrow R \) models the benefit of player \( i \) over action profiles.

For an action profile \( a = (a_1, a_2, \ldots , a_n) \in A \), \( a_{-i} = \{ a_1, \ldots , a_{i-1}, a_{i+1}, \ldots , a_n \} \) denotes the action profile of all players other than player \( i \). Therefore, the action profile \( a \) can be represented as \( (a_i, a_{-i}) \). Similarly, the utility function \( U_j(a) \) is represented by \( U_j(a_i, a_{-i}) \). The concept of (pure) Nash equilibrium (NE) is the most important one in game theory. Considering the strategic game \( G \), an action profile \( a^* \in A \) is a pure Nash equilibrium if for all players \( i \in N \) and for all \( a_i \in A_i \) it holds that \( u_i(a_i, a_{-i}^*) \geq u_i(a_i, a_{-i}^*) \). Simply speaking, Nash equilibrium is a set of strategies in which each player does not benefit from the one-sided change.

The strategic game \( G \) is an exact potential game [25] with potential function \( \phi : A \rightarrow R \) if for every player \( i \in N \), for every \( a_{-i} \in A_{-i} \), and for every \( a_i, a_i' \in A_i \),

\[
\phi(a_i, a_{-i}) - \phi(a_i', a_{-i}) = u_i(a_i, a_{-i}) - u_i(a_i', a_{-i})
\]  

(1)

The existence of NE in an exact potential game is guaranteed [26]. Also, it can easily be proved that any action profile that maximizes the potential function is a Nash equilibrium.

IV. THE PROPOSED ALGORITHM

In this section, we design a potential game to adjust the radius of the sensors from their random initial positions to a valuable configuration by taking into account both the worth of the covered area and the energy consumption. The payoff-based learning algorithm is employed to update the agents’ actions.

A. Problem Formulation

Suppose several sensor nodes (players) \( S = \{s_1, s_2, \ldots , s_N\} \) are randomly deployed in a given area. Sensors are static with a variable sensing radius between \( r_{\text{min}} \) and \( r_{\text{max}} \). We assume that the communication range of each sensor \( i \) (\( R_i \)) is at least twice the \( r_{\text{max}} \). Thus, each sensor can transmit state information to its neighbors and interact with its neighbors. The purpose is to cover the maximum number of targets in the area while the consumed energy is minimized. Therefore, the sensors try to adjust their sensing radius for two purposes: first, maximizing the total worth of the covered area. Secondly, minimizing the total energy consumption caused by sensing. The worth of the points is expressed with the probability of the occurrence of an event in those points. We designed a game to optimize the coverage of the points. There are several points \( q = (q_x, q_y) \) in the desired area. The collection of all points is denoted by \( Q \). A numerical variable \( f_q \geq 0 \) is assigned to the worth or the probability of the occurrence of an event at each point. The value \( f_q \) is recognized as a benefit of observing the point \( q \). Therefore, our objective is defined as follows:

Maximize \( (\sum_{q \in Q} f_q - \sum_{j=1}^{N} E_j^{\text{sense}}(r_j)) \)  

(2)

Subject to: \( r_j \in [r_{\text{min}}, r_{\text{max}}] \)  

(3)

In the objective function (2), \( E_j^{\text{sense}}(r_j) \) is the energy consumed by sensor node \( j \) due to sensing work. It is proportional to \( r_j^2 \), where \( r_j \) is the sensing radius of the working node [27].

Suppose \( N \) static sensor nodes are randomly deployed in the region. Sensors are fixed however they can adjust their sensing radius. The sensing radius of agent \( i \), at time step \( t \) is denoted by \( a_i(t) \), and the area covered by agent \( i \) at time step \( t \) is shown by \( s(a_i(t)) \).
Each agent $i$ choose the radius $a_i(t)$ from a discrete set within $r_{\min}$ and $r_{\max}$. Thus, the action of the agent $i$ at time step $t$ is $a_i(t)$, where $a_i(t) \in A_i(t)$ and $A_i(t)$ is the available action set for agent $i$, at time step $t$. The action profile of all agents is denoted by $a(t) = (a_i(t),...,a_N(t)) \in A(t) := \prod_{i=1}^{N} A_i(t)$.

### B. Utility Design

To formulate the utility function, we consider energy consumption and coverage. The energy consumption of agent $i$ due to sensing is defined as

$$E_i^{\text{sense}}(a_i(t)) = k_i(a_i(t))^2$$

(4)

Where $k_i > 0$. Increasing the radius will increase energy consumption. Hence $a_i(t)$ is used as an optimization variable, where each agent attempts to optimize its power usage by finding a proper radius. by considering $r_{\min} = 0$, our proposed method can determine if some sensors to be in sleep mode. Agent $i$ can choose $a_i(t) = 0$ when the agent cannot improve the sensing performance of points.

The utility function of agent $i$, $U_i$, is shown in (5) which is designed to capture the tradeoff between the worth of covered area and the energy consumption by agent $i$:

$$U_i(a(t)) = F(a(t)) - E_i^{\text{sense}}(a_i(t)) - E_i^{\text{sense}}(a_i(t))$$

(5)

Where $a_i^0(t)$ indicates that agent $i$ is in sleep mode and $a_{-i}(t)$ is the action of all agents other than agent $i$, and

$$F(a(t)) = \sum_{q \in \bigcup_{i \in Q} S(a_i(t))} f_q$$

(6)

$F(a(t))$ denotes the worth of the covered area by the agents. Therefore, $F(a(t)) - F(a_i^0(t),a_{-i}(t))$ is the marginal contribution of the agent $i$ of sensing the covered area. The following lemma shows that our defined game is potential.

**Lemma 1.** The strategic game $G = (N,A,U)$ is an exact potential game with the potential function

$$\phi(a(t)) = F(a(t)) - \sum_{j=1}^{N} E_j^{\text{sense}}(a_j(t))$$

(7)

**Proof:**

As shown in [17], a potential game has to satisfy the following condition.

For any agent $i = 1,...,N$ and action $a_i'(t) \in A_i$, equation (1) is established.

According to (5) and (7), we have

$$\phi(a_i'(t),a_{-i}(t)) - \phi(a(t)) = F(a_i'(t),a_{-i}(t)) - E_i^{\text{sense}}(a_i'(t)) - E_i^{\text{sense}}(a_i(t))$$

Thus (8) shows that (1) holds.

### C. Distributed Learning Algorithm

Converging on a solution such as a Nash equilibrium requires distributed adaptation rules. The motivation for using these adaptation rules is that each agent can maximize its utility function using these rules. Game-theoretic reinforcement learning provides a starting point for the construction of iterative algorithms to reach a Nash equilibrium.

The utility for each sensor is obtained based on the actions taken by other sensors. On the other hand, we assume that each sensor is only aware of the status of its surrounding targets. Therefore, due to such information constraints, the nodes are unable to calculate the payoff associated with alternative actions.

To solve the potential game proposed in the previous section, we propose a reinforcement learning algorithm that is implemented by Algorithm 1. In this algorithm, at each time step $t$, each sensor repeatedly updates its action synchronously, either trying some new action in the possible action set or selecting the action which corresponds to highest amount of utility from the time step $0$ to $t-1$.

#### Algorithm 1 Payoff-based sensing radius adjustment algorithm.

1. At step $t=0$, each player selects and plays any action $a_i(0) \in A_i$. Thus we will get the baseline action profile and baseline utility $[\bar{a}(1) = a(0), \bar{u}(1) = u(0)]$.

2. In subsequent steps, each agent selects his baseline action with probability $1-\varepsilon$ or experiments a new random action with probability $\varepsilon$:
   - $a_i(t) = \bar{a}_i(t)$ With probability $1-\varepsilon$.
   - $a_i(t)$ is chosen randomly over $A_i$ with probability $\varepsilon$.

3. Baseline action profile and baseline utility update:
   - If $\phi(a(t)) > \bar{u}(t)$, then $\bar{a}(t+1) = a(t)$
   - If $\phi(a(t)) \leq \bar{u}(t)$, then $\bar{a}(t+1) = \bar{a}(t)$

4. Return to step 2 and repeat.
V. SIMULATION RESULTS

Consider a $50 \times 50$ target area where a group of fifty sensors ($N=50$) is randomly deployed in this area. Sensors are fixed and each sensor can choose its $a_i$ from the set $\{0,1,2,\ldots,10\}$, which means $r_{\text{min}} = 0$ and $r_{\text{max}} = 10$. We are considering 10 targets that are located randomly in the area. The value of all the points is the same and equal to $\frac{1}{10}$. The simulation parameter is chosen as $k_i=3 \times 10^{-5}$. We choose $\varepsilon = \left(\frac{1}{t+2\times10}\right)^2, 0.1, 0.01$ in our simulation. Initially, the sensing radius of all sensors is zero $a_i=0$. Fig. 1 shows the initial configuration of the sensors. Fig. 2 presents the configuration in iteration 5000. According to Fig. 2, in addition to full coverage of the points, energy consumption in the area has decreased due to the setting sensor radius of all nodes. The evolution of the potential function for $\varepsilon = \left(\frac{1}{t+2\times10}\right)^2, 0.1, 0.01$ in each iteration is shown in Fig. 3 which confirms that the sensors are close to the Nash equilibrium. Comparisons show that the algorithm converges to both diminishing and fixed exploration rates, and Nash equilibrium is obtained. The results show that the convergence rate for $\varepsilon = 0.01$ is less than $\varepsilon = 0.1$.

Fig. 4 and Fig. 5 depict the coverage ratio and energy consumption due to sensing with different sensor nodes. When the number of sensor nodes is small, although energy consumption is reduced, optimal coverage is not achieved in the area.

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Figure 1. The initial configuration of the network where “•” and “+” are sensor nodes and targets, respectively.

Figure 2. The final configuration of the network in iteration 5000.

Figure 3. The evaluation of the potential function in various exploration rates.

Figure 4. Coverage ratio vs. node density.
To validate the claims, we compared our proposed algorithm with OGDC [6]. Consider a $50 \times 50$ square in which each grid is $1 \times 1$. The goal is to cover the center of all grids. Our proposed algorithm can adjust the sensor radius, the sensing radius used in OGDC is 8 and 10 m. Sensor nodes are randomly deployed in the area. We vary the number of sensors between 50 and 1000. The performance comparison between our proposed algorithm and OGDC is shown in Fig. 6 and Fig. 7. To achieve the same coverage rate, our proposed algorithm needs fewer nodes than OGDC. Also, we can see that OGDC cannot perform complete coverage. Therefore, our proposed method ensures a better coverage rate than OGDC by adjusting the sensing radius.

**VI. CONCLUSION**

We modeled the sensor radius adjustment problem as a potential game. The goal of the game is to cover the desired targets and reduce the energy consumption of sensor nodes. So, we designed the utility function to meet these two goals. Then, we presented a payoff-based learning algorithm to solve the game and achieve a Nash equilibrium. The performance of our proposed algorithm was evaluated via simulations and compared to OGDC. The simulation results show that our proposed algorithm can activate the minimum sensor nodes as well as adjusting their sensing radii, thus cost less energy consumption, and achieve a better performance than OGDC.

**REFERENCES**


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