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A centralized immune-Voronoi deployment algorithm for coverage maximization and energy conservation in mobile wireless sensor networks

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ABSTRACT

Saving energy is a most important challenge in Mobile Wireless Sensor Networks (MWSNs) to extend the lifetime, and optimal coverage is the key to it. Therefore, this paper proposes a Centralized Immune-Voronoi deployment Algorithm (CIVA) to maximize the coverage based on both binary and probabilistic models. CIVA utilizes the multi-objective immune algorithm that uses the Voronoi diagram properties to provide a better trade-off between the coverage and the energy consumption. The CIVA algorithm consists from two phases to improve the lifetime and the coverage of MWSN. In the first phase, CIVA controls the positions and the sensing ranges of Mobile Sensor Nodes (MSNs) based on maximizing the coverage and minimizing the dissipated energy in mobility and sensing. While the second phase of CIVA adjusts the radio (sleep/active) of MSNs to minimize the number of active sensors based on minimizing the consumption energy in sensing and redundant coverage and preserving the coverage at high level. The performance of the CIVA is compared with the previous algorithms using Matlab simulation for different network configurations with and without obstacles. Simulation results show that the CIVA algorithm outperforms the previous algorithms in terms of the coverage and the dissipated energy for different networks configurations.

1. Introduction

In recent years, Wireless Sensor Networks (WSNs) have found to monitor the environment, track targets on a battlefield, measure traffic on roads, monitor patients or track the location of personnel inside buildings [1]. One of the key points in the design of WSNs that is related to the sensing attribute is the coverage of the sensor field. Coverage has a direct effect on the network performance, thus it considered as the measure of quality of service in WSNs. The deployment strategy of sensor nodes in the field is the most critical factor related to the coverage and the connectivity. Sensors can be deployed either randomly or deterministically. Random deployment is usually preferred in large scale WSNs not only because it is easy and less expensive but also because it might be the only choice in remote and hostile environments. However, random deployment is not efficient approach and can cause coverage holes in the field. On the other hand, deterministic deployment is very complex in large and harsh environments and costs time [2].

Rearrangement the sensor nodes after initial deployment by attached them with vehicles or mobile robots can improve the network coverage and eliminate the coverage holes. However, moving the sensor nodes introduces new challenges in saving the consumption energy because the mobility systems of nodes consume more energy [3]. Thus, many deployment algorithms based on a binary sensing model [1,2,4–9] and a probabilistic sensing model [10–12] have been developed recently to improve the network coverage. Some of these algorithms took in their consideration the mobility cost of all nodes besides improving the coverage, while other algorithms considered the sensing range adjustment to save the dissipated energy in sensing and improve the coverage. However, these is no deployment algorithm considers the dissipated energy in the mobility, the sensing and the redundant coverage at the same time besides improving the network coverage. In order to provide a better trade-off between the coverage and the energy consumption, one of the recently evolutionary algorithms which called the Multi-Objective Immune Algorithm (MOIA) is considered here. The main features of MOIA algorithm compared to other algorithms are [13,14]: (1) It is the global search performance; (2) It produces the solution sets that are highly competitive in terms of convergence, diversity and distribution; (3) It has elitism which inherently embedded in the selection mechanism to preserve good solutions and not lose them during generations;

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(4) It adapts the population to a reasonable size for the specific problem and this reduces the number of objective function calls; and (5) It has much less computational cost.

This paper proposes a new energy-efficient deployment algorithm based on mixing the multi-objective immune algorithm [7,13–16] and Voronoi diagram [4,6,17] called a Centralized Immune-Voronoi deployment Algorithm (CIVA) to improve the coverage and the lifetime of WSNs. CIVA relocates the Mobile Sensor Nodes (MSNs) based on controlling the mobility, the sensing range and the radio (i.e. active/sleep) of each one to maximize the coverage using an optimal number of sensors and concurrently, save the dissipated energy in mobility, sensing and redundant coverage. The paper is organized as follows. Section 2 is a literature survey about various deployment algorithms. The problem of coverage-energy is stated in Section 3. Section 4 explains the formulation of the coverage-energy problem. The details of the proposed CIVA algorithm will be presented in Section 5. Section 6 discusses the analysis of the CIVA algorithm. In Section 7, the simulation results and discussion are given. Section 8 offers some conclusions.

2. Related work

Many coverage maximization algorithms based on a binary model for WSNs have appeared in the literature [1,2,4–9]. In [1] authors utilized a multi-objective genetic algorithm to relocate the MSNs in order to provide the trade-off between coverage and nodes' travelled distance. An optimization scheme based on a multi-objective evolution algorithm is adopted in [2] to increase the coverage rate and to reduce the energy consumption of sensing by adjusting the positions and the sensor ranges of the nodes. But authors here neglected the consumption energy in the mobility of all MSNs. A deployment algorithm called PSO_Voronoi based on Particle Swarm Optimization (PSO) and Voronoi diagram was presented in [4] to enhance the coverage of WSNs. PSO is used to find the optimal deployment of sensors that gives the best coverage while Voronoi diagram evaluates the fitness of the solution. Authors in [5] developed a new version of PSO_Voronoi algorithm based on the penalty function called WSNPSOcon. WSNPSOcon uses PSO to solve the optimization problem by finding the best locations of the sensor nodes subject to maximize the network coverage and limit the maximum moved distance by any sensor to the threshold value. The performance of WSNPSOcon algorithm affects by the value of the penalty parameter.

A distributed self-relocation algorithm based on the average relative position between pairs of sensors was introduced in [6]. This algorithm consists of three phases to relocate the randomly deployed sensors and perform a sensing range adjustment using Voronoi diagram so that an optimized coverage is achieved with minimum consumption of energy. In [7] authors developed a deployment algorithm based on the multi-objective immune algorithm. This algorithm redeploys MSNs based on maximizing the coverage area and minimizing the mobility cost of all nodes. A coverage control scheme based on elitist Non-dominated Sorting Genetic Algorithm (NSGA-II) was introduced in [8] for the heterogeneous WSNs. NSGA-II is used to minimize the sensing ranges of the active sensors, while satisfying the coverage requirements based on adjustable sensing range property of the static sensor nodes. Authors in [9] introduced an algorithm for nodes self-deployment aimed at maximizing the coverage of WSN based on neural networks and genetic algorithms. The developed algorithm uses a neural network as a controller for nodes mobility, when the objective is to maximize the coverage area and minimize the number of time steps to achieve the objective, while a genetic algorithm for the training of the neural network through reinforcement learning.

Since the binary coverage model is not a realistic model, therefore probabilistic based coverage algorithms have appeared recently [10,12] to improve the coverage of WSNs. In [10], Quantum-inspired Cultural Algorithm (QCA) has been adopted to maximize the coverage area of WSNs based on a probabilistic sensing model. Dual evolution structure is introduced in this algorithm to increase the observed probability. QCA is used to solve the coverage optimization problem of WSN so as to obtain maximum coverage ratio and minimum redundancy ratio with better solution precision. Authors in [11] adopted two algorithms for improving the coverage of WSN based on a probabilistic model. The first algorithm (PSO-S) is based on Particle Swarm Optimization (PSO) and Virtual Forces Algorithm (VFA) to develop a totally distributed algorithm, which only requires the flying robots to receive local information from the neighbors to update their velocity and trajectory. While the second algorithm (VFA-D) acts as the distributed implementation of VFA algorithm. These two algorithms considered the coverage and the travelled distances in their objective function. A hybrid sensor deployment algorithm for WSNs called CSAPO which combines Clonal Selection Algorithm (CSA) with Artificial Physics Optimization (APO) has been presented in [12]. APO is used to update the overall objective while the CSA is used to enable APO to escape from local optima. CSAPO algorithm maximizes the coverage area of WSN and decreases the consumption energy in the moving process. It is cleared that there is no algorithm considers the dissipated energy in the mobility, the sensing and the redundant coverage at the same time besides improving the coverage.

3. Coverage-energy problem statement

The maximization of the network lifetime does not depend only on maximizing the coverage, but also depends on minimizing the dissipated energy. The sensor nodes should be redeployed subject to maximize the coverage and minimize the dissipated energy in mobility, sensing and redundant coverage. The problem is redeployment the sensor nodes to provide a better trade-off between the coverage and the energy consumption. This problem will be solved by considering the Multi-Objective Immune Algorithm (MOIA) [7,13–16] to activate an optimal number of sensors with minimum sensing ranges subject to cover the entire field and limit the moving cost and by utilizing the Voronoi Diagram (VD) [4,6,17] to adjust the sensing range of each sensor in the network.

4. Formulation of coverage-energy problem

In this section we formulated the coverage-energy problem as a mathematical problem. Define that the size of the sensor field is $m \times n$ contains N MSNs ($S = \{s_1, s_2, \ldots, s_i, \ldots, s_N\}$) with the sensing radius set ($R_S = \{R_{S1}, R_{S2}, \ldots, R_{Si}, \ldots, R_{SN}\}$), where $R_{Si} \in [R_{S_{min}}\ R_{S_{max}}]$. To formulate the problem, the following assumptions about MSNs are fixed:

- All sensors have the ability to adjust its sensing range within the range $[R_{S_{\min}} R_{S_{\max}}]$.
- The communication range (R_{ci}) of each sensor (s_i) is set at least by $2R_{Si}$ to guarantees the network connectivity [18,19].
- All sensors are mobile and location-aware using localization algorithms [20,21].
- Obstacles can be detected by sensors.

4.1. Coverage rate calculation

There are mainly two types of coverage sensing models. The first one is a binary model, which is supposed to be covered as much as possible. Assume the sensor field is divided into $m \times n$ grids and each grid size is equal to 1 as shown in Fig. 1. The coverage of the whole area is proportional to the number of grid points that can be covered. Considering the grid point $G(x, y)$, the possibility that it can be covered by a sensor $s_i(x_i, y_i)$ based on the binary model is described by [1,2,4–9]:

$$P(x, y, s_i) = \begin{cases} 1, & \text{if } \exists\, i \in \{1, \ldots, N\}, \quad d(s_i, G) \le R_{S_i} \\ 0, & otherwise \end{cases} \tag{1}$$