EFFICIENT DEPLOYMENT OF SENSORS IN WIRELESS SENSOR NETWORK: A SURVEY

Abstract: Wireless Sensor Network consists of spatially distributed autonomous sensors to monitor physical or environmental conditions, such as temperature, sound, pressure, etc. and to cooperatively pass their data through the network to a main location. The full area coverage sensor deployment problem is a challenging issue in wireless sensor networks. This paper focused on sensor deployment strategies that aim to acquire a full-coverage state with a minimum number of sensors in a predetermined target region.

Keywords: Wireless Sensor Network; Deployment; Full Area Coverage

I. INTRODUCTION

The WSN is built of "nodes" – from a few to several hundreds or even thousands, where each node is connected to one (or sometimes several) sensors. Each such sensor network node has typically several parts a radio-transceiver with an internal antenna or connection to an external antenna, a microcontroller, an electronic circuit for interfacing with the sensors and an energy source, usually a battery or an embedded form of energy harvesting. Size and cost constraints on sensor nodes result in corresponding constraints on resources such as energy, memory, computational speed and communications bandwidth. The topology of the WSNs can vary from a simple star network to an advanced multi-hop wireless mesh network. The propagation technique between the hops of the network can be routing or flooding. Due to the unique many-to-one (converge-cast) traffic patterns, the traffic of the whole network will be converge to a specific set of sensor nodes (e.g., neighboring nodes of the sink) and results in the hotspot problem. However, as long as the sink and sensor nodes are static, this issue cannot be fully tackled. Therefore, there is a recent trend to exploit mobility of the sink as a promising approach to the hotspot problem.

II. PROBLEM DESCRIPTION

Full-area coverage in the predetermined target region is a challenging issue in wireless sensor network. Appropriate sensor deployment is required to perform surveillance and monitoring tasks successfully because a sensor has resource constraints, such as a physical sensing range, a battery power limit and a limited memory; as a result, a sensor can cover only a small part of the region of interest. Coverage can be considered to be a measure of quality of the services or tasks. Most of the existing approaches provide full-area coverage perfectly only in free space. Instead of fully random deployment and deterministic deployment, meta-heuristic search algorithms have been applied to various sensor deployment strategies. Sensor deployment is formulated as a search problem to minimize the number of deployed sensors as well as to maximize the coverage of the sensors similar to the mathematical approach.

III. LITERATURE REVIEW

A) ORRD Algorithm

Sensor nodes should be efficiently deployed in a predetermined region in a low-cost and high coverage manner. Random deployment is the simplest way to deploy sensor nodes but may cause unbalanced deployment and, therefore, increase hardware costs and create coverage holes. ORRD (Obstacle Resistant Robot Deployment) algorithm which involves the design of a node placement policy, a serpentine movement policy, obstacle-handling rules, and boundary rules. The robot explores the environment and deploys a stationary sensor on the target location from time to time. Robot deployment can achieve full coverage with fewer sensors and increase the sensing effectiveness of stationary sensors to guarantee full coverage and connectivity. In addition, the robot may perform other missions such as hole detection, redeployment, monitoring, and so on. However, the unpredicted obstacles can challenge robot deployment and make a great impact on the deployment efficiency. It requires much more effort to develop a robot deployment mechanism that uses fewer sensors for full coverage and power efficiency, even though the monitored regions contain unpredicted obstacles. ORRD overcomes the unpredicted obstacles and deploys fewer static sensors but achieves higher coverage percentages compared to existing deployment algorithms.

B) LRV Algorithm

LRV (Least Recently Visited) efficiently and simultaneously solves the problems of coverage, exploration, and sensor network deployment. The basic premise behind the algorithm is that a robot carries network nodes as a payload, and in the process of moving around, emplaces the nodes into the environment based on certain local criteria. In turn, the
nodes emit navigation directions for the robot as it goes by. Nodes recommend directions least recently visited by the robot, hence, the name LRV. The theoretical analysis on graphs and verification in simulation shows that tradeoffs in the assumptions can affect cover time significantly. Simple algorithms like RW or DFS can be used for coverage, but only in the extreme cases as described previously. In the case where mapping and localization are not available but the number of available nodes is unlimited, LRV algorithm appears to outperform others. LRV allows us to deploy and maintain a sensor network, while covering and exploring the environment.

C) MOASA

Various meta-heuristic search methods have been employed to resolve the sensor arrangement problem, which is a type of NP-hard, combinational problem. MOASA (Multi-objective Optimization Approach for Sensor Arrangement) efficiently provides multiple Pareto solutions regardless of the type of maps and sensors in independent trials. MOASA deal with four unknowns to define the sensor arrangement problem more practically: 1) The number of sensors is unknown, 2) no candidate is given for installation, 3) the coverage radii of sensors are variable, and 4) sensors cover a wide area in which obstacles exist in complicated arrangements. MOASA without the hybrid optimization scheme shows a slow convergence property in terms of the distance from the Pareto front. On the other hand, it is shown that MOASA without hierarchical fitness assignment provides better solutions near the Pareto front in comparison with the MOASA without hybrid optimization. However, the solutions obtained from the MOASA without hierarchical fitness assignment are still inferior to the Pareto solutions given by the MOASA under the same conditions.

D) OSRCEA

Coverage-Enhancing Algorithm based on overlap-sense ratio (OSRCEA) for a given region assumes that the parameters of neighboring sensors are known, the parameter of \( \text{OSR} \) is introduced to represent the whole impact of neighboring sensors. Subsequently, the relationship between the OSR and rotation angle is quantized by a novel algebraic expression, which guarantees that the node with larger overlapping region will turn greater angle. Accordingly, it achieves enhancement of network coverage as well as reduction of computational complexity. In addition, a modified strategy of shutting off redundant sensors is proposed to prolong the network lifetime. By adjusting the sensing direction of the nodes, the coverage area is increased with the reduction of computational complexity. In addition, a modified strategy is presented to shut off the redundant sensors so that network lifetime is prolonged. Combining OSRCEA with modified strategy of shutting off redundant sensors, the coverage is greatly enhanced and the energy of redundant sensors is saved.

E) BPSO

The visual coverage is defined by realistic and consistent assumptions taking into account camera characteristics. In total, nine evolutionary-like algorithms based on Binary Particle Swarm Optimization (BPSO), Simulated Annealing (SA), Tabu Search (TS) and genetic techniques are adapted to solve this visual coverage based camera network placement problem. Networking these cameras deployed at judicious locations should guarantee coverage as well as image quality to the networked video streams. Sensor network placement is formulated to satisfy coverage constraints based on the area to be covered, area versus discrete points) and the deployment mechanisms (random versus deterministic). Identifying an optimal configuration of multiple sensors in order to observe the maximum space is a combinatorial optimization problem that is NP-hard. This means that simple enumeration and search techniques will meet a great difficulty in determining optimal placement configurations. Placement of networked surveillance cameras requires optimizing their configurations using an optimization technique with a visibility analysis across the monitored area. BPSO inspired probability (BPSO-IP) based approach optimize the spatial visual coverage of a 2-D and 3-D security monitoring environment. BPSO-IP, solve coverage problems especially for large scale dimensions where techniques such as Binary Integer Programming can explode in terms of memory and computing time.

F) D-Tri Algorithm

Wireless visual sensor networks (WVSNs) can not only provide monitoring functions like wireless sensor networks but also capture images of the monitored area. This is why the barrier coverage problem in WVSNs has received attention from many researchers. For WVSNs consisting of camera sensors with rotation capability, the enhanced Distributed \( \beta \)-breadth belt-barrier construction algorithm with rotation (D-TriBR) algorithms can not only reduce the number of camera sensors required to construct a barrier but also ensure that any barrier with \( \beta \)-QoM in the network can be identified. D-TriBR is also used to minimize the number of sensors required. Moreover, the back track mechanism can identify the barrier with \( \beta \)-QoM in the area if there is any. The lower the \( \beta \) requirement, the higher successful rate. That is, the successful rate of barrier construction declines with the increase of \( \beta \). The main advantage of this method is that any barrier existent in the network can be identified. Its main weakness is that broadcasting of BREQ messages may
result in a large overhead of data transmission and considerable packet collisions.

G) ACB-SA
Sensors in most wireless sensor networks (WSNs) work with batteries as their energy source, it is usually infeasible to recharge or replace batteries when they discharge. Thus, solving the efficient-energy coverage (EEC) problem is an important issue for a WSN. Therefore, it is necessary to schedule the activities of the devices in a WSN to save the network’s limited energy and prolong its lifetime. Ant Colony- Based Scheduling Algorithm (ACB-SA) to solve the EEC problem. By scheduling the devices’ activities from active to sleep, or vice versa, these methods can prolong the lifetime of the WSN by more efficient use of the limited amount of energy. Eventually, to achieve a longer lifetime, it will be important to find the maximum number of disjointed subsets of devices by this scheduling method. The traditional scheduling algorithms that use the ACO algorithm simply follow the lead of the previous solutions, and they are not optimized to solve the EEC problem. However, the performance of the ACO algorithm is determined by how it initializes the pheromone field and how it makes the construction graph reflect the characteristics of the problem. To improve the performance of the Ant-Colony-Based Scheduling Algorithm, we applied a new initialization method for the pheromone field and the modified construction graph. In addition, the ACB-SA, unlike conventional ACO algorithms, does not consider what values are needed for the user parameters $\alpha$ and $\beta$.

H) ACO Algorithm
The Efficient-Energy Coverage (EEC) problem is an important issue when implementing Wireless Sensor Networks (WSNs) because of the need to limit energy use. ACO (Ant-Colony Optimization) algorithm has a unique characteristic that conventional ACO algorithms do not have. The proposed ACO algorithm (Three Pheromones ACO, TPACO) uses three types of pheromones to find the solution efficiently, whereas conventional ACO algorithms use only one type of pheromone. One of the three pheromones is the local pheromone, which helps an ant organize its coverage set with fewer sensors. The other two pheromones are global pheromones, one of which is used to optimize the number of required active sensors per Point of Interest (PoI), and the other is used to form a sensor set that has as many sensors as an ant has selected the number of active sensors by using the former pheromone. The TPACO algorithm has another advantage in that the two user parameters of ACO algorithms are not used. We also introduce some techniques that lead to a more realistic approach to solving the EEC problem. The first technique is to utilize the probabilistic sensor detection model. The second method is to use different kinds of sensors, i.e., heterogeneous sensors in continuous space, not a grid-based discrete space. Under extreme circumstances, the TPACO algorithm can solve the EEC problem with a more realistic approach.

I) BEFAC
Full-area coverage in the predetermined target region is a challenging issue in wireless sensor network. The existing approaches provide full-area coverage perfectly only in free space. Instead of fully random deployment and deterministic deployment, meta-heuristic search algorithms have been applied to various sensor deployment strategies. Sensor deployment is formulated as a search problem to minimize the number of deployed sensors as well as to maximize the coverage of the sensors similar to the mathematical approach. By applying the Bi-population- based Evolutionary algorithm for Solving Full Area Coverage problems (BEFAC), a full-coverage state is acquired with a minimum number of deployed sensors in the target region, which has non-penetrable obstacles, and the algorithm avoids getting caught in local minima. Solutions of the full-coverage population are evolved in an attempt to reduce the number of overall deployed sensors while retaining the full-coverage state. In contrast, the solutions of the partial coverage population have evolved in an attempt to increase the coverage rate without deploying more sensors. A combination of these different populations could lead to increasing the genetic diversity of the sensor deployment solutions while avoiding local optima and using a smaller amount of computation.

IV. CONCLUSION
In this paper a survey on wireless sensor deployment has been performed. Appropriate sensor deployment is required to perform surveillance and monitoring tasks successfully because a sensor has resource constraints, such as a physical sensing range, a battery power limit and a limited memory; as a result, a sensor can cover only a small part of the region of interest. A whole region of interest should be covered by a combination of many sensors, which accomplish their own tasks or applications. Inefficient sensor deployment could lead to a low coverage rate and poor performance. Therefore, it is important to select an algorithm which is capable of providing full-area coverage with minimum number of deployed sensors in a target region.
REFERENCES


