Efficient Heuristic for the Deterministic Deployment of Wireless Sensor Networks

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1 Introduction

Sensor deployment, which often dictates the overall network performance, is a fundamental issue in Wireless Sensor Networks (WSNs). In this paper, we address the problem of deterministic wireless sensor networks deployment. Our research aims to generate the best network topology that ensures the required degree of coverage with the minimum number of sensors. The problem in hand is NP-complete. To overcome the great complexity involved, we propose an efficient deterministic greedy heuristic named Max-Cov-Tp that is able to determine the minimum number of sensors and their locations to achieve the overall coverage of the Region of Interest (RoI).

2 Assumptions and problem formalization

We assume that targets/events appear at a set of known locations referred to as targets points defining the set $T \subseteq RoI$. We constrain the deployment of sensors in the set $D \subseteq RoI$ consisting of deployment points in the RoI. We consider the truncated attenuated disk coverage model [4], and we assume that each target point $p \in T$ is associated with a required minimum event detection probability threshold, denoted by R_p. Thus, the objective of our deployment problem is that $\forall p \in T$, the measured event detection probability of that point, M_p, must be greater than or equal to R_p. More formally, the WSNs deployment problem can be formalized as follows.

$$\begin{aligned} \min \; & \sum_{p \in D} x_p \\ \text{s.t. } & M_p \geq R_p, \;\; \forall p \in T \\ & x_p = 0 \; or \; 1, \;\; \forall p \in D. \end{aligned}$$

This problem is a Binary Integer Programming problem which is NP-complete [3].

3 Our proposal

The proposed algorithm called Max-Cov-Tp is an iterative algorithm that deploys one sensor at each iteration. Max-Cov-Tp proceeds according to the same fundamental principle of Min-Miss algorithm [1], which exploits the anticipating deployment to decide where to place a new sensor. The anticipation process is materialized by simulating the sensor deployment in all candidates points Ap (free deployment points) and the best position is then selected. The fundamental difference with Min-Miss lies in the choice of the best position. While Min-Miss selects the best position by minimizing a metric called over miss probability, Max-Cov-Tp selects the position that maximizes the number of covered target points. The main advantage of the Max-Cov-Tp algorithm consists in avoiding the maximization of the detection probability of target points that have been already covered which reduces the deployment cost. The Max-Cov-Tp pseudo-code is given in Algorithm 1.

4 Obtained results

To quantify the benefit of our approach, we compare Max-Cov-Tp with four state-of-the-art deployment approaches, namely: Min-Miss [1], Min-Max-Cov [5], BDA [3], and GEBDA [2]. Min-Max-Cov is a greedy heuristic, BDA is based on the Tabu search metaheuristic, and GEBDA is a genetic algorithm. Two scenarios are considered: uniform coverage and preferential coverage.

Algorithm 1 Max-Cov-Tp

$num\_sensors = 1$
$Ap = D$
repeat
  for (every deployment point $p \in Ap$) **do**
    Simulate the placement of a sensor in p
    Compute the number of covered target points
  end for
  Place a sensor on p that maximizes the number of covered target points
  $Ap = Ap - \{p\}$
  $num\_sensors = num\_sensors + 1$
until (T is covered) **or** ($num\_sensors > availableSensors$)

4.1 Evaluation stage 1: Uniform coverage requirement

The algorithms were tested on three uniform coverage scenarios. In scenarios 1, 2, and 3, an event detection probability equal to 0.3, 0.6, and 0.9, respectively, in the whole RoI (25×25) is required.

Table 1. Stage 1 simulations results.

Deployment strategy	**Scenario 1 (0.3)**		**Scenario 2 (0.6)**		**Scenario 3 (0.9)**	
	No. of sensors	Satisfaction rate	No. of sensors	Satisfaction rate	No. of sensors	Satisfaction rate
Max-Cov-Tp	33	100 %	55	100%	81	100%
Min-Miss	41	100%	62	100%	100	100%
GEBDA	33	100%	57	100%	109	100%
Min-Max-Cov	44	100%	66	100%	130	100%
BDA	40	96.96%	58	94.56%	134	97.28%

The obtained results (Table 1) show that Min-Max-Cov, Min-Miss, GEBDA, and BDA need more sensors than our proposal Max-Cov-Tp to achieve the same performance.

4.2 Evaluation stage 2: Preferential coverage requirement

In this scenario, we assume that the requested geographic distribution for required minimum event-detection probability thresholds is generated according to multivariate normal distribution, as done in [2, 3].

We observed that BDA cannot guarantee full area coverage even with a high number of iterations. The obtained results show that, for a full satisfaction rate, Max-Cov-Tp deployed 49 sensors, less of 5 than GEBDA which placed 54 sensors. Min-Miss deployed 104 sensors, and Max-Min-Cov placed 115 sensors. Thus, Max-Cov-Tp algorithm provides better results than other heuristics proposed in literature.

References

1. Y. Zou and K. Chakrabarty, "Uncertainty-aware and coverage-oriented deployment for sensor networks", J. Parallel Distrib. Comput, vol. 64, pp. 788-798, 2004.
2. M. R. Senouci, "On the use of the belief functions theory in the deployment and control of wireless sensor networks", PhD thesis, USTHB/UPEC, 2014.
3. N. Aitsaadi, N. Achir, K. Boussetta and G. Pujolle, "A Tabu-Search WSN Deployment Method for Monitoring Geographically Irregular Distributed Events", Sensors journal, 2009.
4. B. Wang, "Coverage Control in Sensor Networks", Springer, 2010.
5. S. Dhillon and K. Chakrabarty, "Sensor placement for effective coverage and surveillance in distributed sensor networks", In Proc. IEEE WCNC, volume 3, pp. 1609-1614, 2003.