Topography-Aware Sensor Deployment Optimization with CMA-ES

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Abstract. Wireless Sensor Networks (WSN) have been studied intensively for various applications such as monitoring and surveillance. Sensor deployment is an essential part of WSN, because it affects both the cost and capability of the sensor network. However, most deployment schemes proposed so far have been based on over-simplified assumptions, where results may be far from optimal in practice. Our proposal aims at automating and optimizing sensor deployment based on realistic topographic information, and is thus different from previous work in two ways: 1) it takes into account the 3D nature of the environment ; 2) it allows the use of anisotropic sensors. Based on the Covariance Matrix Adaptation Evolution Strategy (CMA-ES), the proposed approach shows good potential for tackling diverse problems in the WSN domain. Preliminary results are given for a mountainous area of North Carolina where coverage is maximized.

1 Introduction

In recent years, Wireless Sensor Networks (WSN) have been studied intensively for various applications such as environmental monitoring and surveillance. A WSN usually consists of numerous wireless devices deployed in a region of interest, each able to collect and process environmental information and communicate with neighbour devices [2, 9, 19].

Sensor deployment is an essential issue in WSN, as it affects how well a region is monitored by sensors. Considering a region monitored by sensors, one of the most critical issues is the region coverage [9, 11–13, 19, 20]. One goal of a WSN is that each location in a region should be within the sensing range of at least one sensor. An alternative approach is to have a region covered simultaneously by at least K sensors [19, 20].

Many deterministic methods have been explored to address the problem of coverage. It has been shown that covering an area with disks of equal radius can be done in an optimal manner [2, 9, 11]. Similar results have been reported when multiple coverage of the target area is required [2, 12, 19, 20]. Besides, the majority of optimization methods proposed are deterministic, and are generally functions of omnidirectional sensor with a fixed sensing range.

However, most suggested methods are based on over-simplified assumptions [12, 14, 15, 19, 20], and the theoretical perfect coverage shown in these deterministic methods may not hold true in practice for a number of reasons. First, most sensor deployment optimization methods assume that sensors are placed on a 2D plane, without taking terrain into account [2, 9, 11]. Second, most deterministic methods suppose that sensors have omnidirectional sensing capabilities, which is generally not accurate [10]. For instance, antennas have different 3D reception area, depending on factors like orientation, distance, and other environmental factors [10].

The disadvantages of deterministic deployment optimization methods are thus evident, and the 100% coverage that they claim is often over-estimated. This issue is critical because it further complicates the problem of sensor deployment: while WSN seems to satisfy the requirements to achieve full coverage on a target area using a deterministic method, the deployers have no means to ensure that this coverage is truly effective in the real environment. This uncertainty of coverage thus presents a challenge in sensor deployment.

Facing this challenge, we follow a more flexible non-deterministic avenue. Our aim is to achieve automated sensor deployment optimization based on realistic topographic terrain information, and realistic sensor modelling. It differs from traditional deterministic methods in that: 1) deterministic schemes only consider 2D environments and ignore the effects of elevation, whereas our method takes into account the 3D terrain information; 2) deterministic schemes usually assume omnidirectional sensors, whereas our method allows for constraints to be applied on sensors, such as limited sensing angles.

In an effort to tackle this more realistic problem, we opt for an evolutionary algorithm approach. Some prior work has been conducted with such paradigms [3, 16], but using more or less the same over-simplifying assumptions as the deterministic approaches. Among available evolutionary algorithms, we chose the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) [8] for its good performance and stability [6, 7]. The position and orientation of the sensors are encoded inside an individual, and a population of individuals is evolved through generations. At the end of the evolution, the individual with the best coverage is chosen as the final solution. This CMA-ES optimization is linked to a Geographical Information System (GIS) to provide essential environmental data such as elevation of region of interest and obstacles in the area, to compute the fitness of individuals.

The remainder of the paper is organized as follows. The problem statement is presented in the next section (Sec. 2), followed by a presentation of the proposed method (Sec. 3). The experimental protocol and results are then summarized (Sec. 4), concluding the paper with discussions and perspectives (Sec. 5).

2 Problem Statement

The main objective of this proposal is to build a realistic model of the environment and sensor network, and to optimize the sensor deployment accordingly. The sensing model depends on distance, orientation, and visibility. We first assume that all sensors are positioned at a certain constant height τ above the ground level. The sensor position is thus described by a 3D point $\mathbf{p} = (x, y, z)$, where (x, y) are free parameters, and $z = g(x, y)$ is constrained by the terrain elevation at position (x, y), as defined by a GIS. We further assume that the anisotropic properties of sensors are fully defined by a pan angle θ around the vertical axis (tilt angle is currently assumed null). Given the GIS, a sensor network $N = \{\mathbf{s}_1, \mathbf{s}_2, \ldots, \mathbf{s}_n\}$ of n sensors is thus fully specified by $3n$ free parameters $\mathbf{s}_i = (\mathbf{p}_i, \theta_i)$, $i = 1, 2, \ldots, n$, with $\mathbf{p}_i = (x_i, y_i)$.

Now the coverage $C(\mathbf{s}_i, \mathbf{q})$ of sensor $\mathbf{s}_i$ at point $\mathbf{q}$ in the environment can be defined as a function of distance $d(\mathbf{s}_i, \mathbf{q}) = ||\mathbf{p}_i - \mathbf{q}||$, angle of view $a(\mathbf{s}_i, \mathbf{q}) = \theta_i - \angle(\mathbf{q} - \mathbf{p}_i)$, and visibility $v(\mathbf{s}_i, \mathbf{q})$ from the sensor:

$$C(\mathbf{s}_i, \mathbf{q}) = f[\mu_d(||\mathbf{p}_i - \mathbf{q}||), \mu_a(\theta_i - \angle(\mathbf{q} - \mathbf{p}_i)), v(\mathbf{s}, \mathbf{q})], \tag{1}$$

where $\angle(\mathbf{q} - \mathbf{p}_i)$ is the pan angle of point $\mathbf{q}$ relative to $\mathbf{p}_i$. For $\mathbf{q}$ to be covered by sensor $\mathbf{s}_i$, it needs to be within its sensing range AND its field of view AND must be visible, that is not blocked by any terrain obstacle such as hills. Let $\mu_d, \mu_a \in [0, 1]$ represent the fuzzy membership functions of the first two conditions, then Eq. 1 can be rewritten as:

$$C(\mathbf{s}_i, \mathbf{q}) = \min \left\{ \begin{array}{c} \mu_d(||\mathbf{p}_i - \mathbf{q}||) \\ \mu_a(\theta_i - \angle(\mathbf{q} - \mathbf{p}_i)) \\ v(\mathbf{s}_i, \mathbf{q}) \end{array} \right\}. \tag{2}$$

Function $v(\mathbf{s}_i, \mathbf{q})$ is usually binary. If the line of sight between $\mathbf{s}_i$ and $\mathbf{q}$ is obscured, then we assume that the coverage cannot be met ($v = 0$), otherwise the visibility condition is fully respected ($v = 1$). Fig. 1 illustrates different scenarios that assume rotational topographic symmetry. For real environments, the visibility induces coverage which can produce many more complex shapes. For instance, Fig. 2 gives a concrete example of an environment and how the visibility condition can affect sensor coverage in this environment.

At each position $\mathbf{q} \in \varXi$ of environment $\varXi$, the coverage for a single sensor is thus the minimum of the three above conditions. Value $C = 1$ means full coverage, and $C = 0$ indicates no coverage. If more than one sensor covers $\mathbf{q}$, then we can compute the local network coverage C_l using:

$$C_l(N, \mathbf{q}) = \max_{i=1,\ldots,n} C(\mathbf{s}_i, \mathbf{q}), \tag{3}$$

and the global coverage C_g using:

$$C_g(N, \varXi) = \frac{1}{|\varXi|} \sum_{\mathbf{q} \in \varXi} C_l(N, \mathbf{q}). \tag{4}$$

Given an environment $\varXi$, the problem statement is thus to determine the sensor network deployment N that maximizes $C_g(N, \varXi)$.

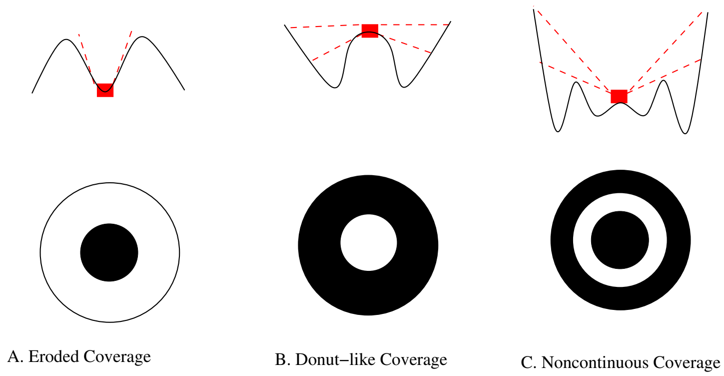


Fig. 1. Examples of visibility induced coverage. The upper row shows different terrain elevations as curves. The small rectangle boxes are sensors. The lower rank shows the true coverage of sensors with those terrain elevations and sensor positions (assuming rotational symmetry).

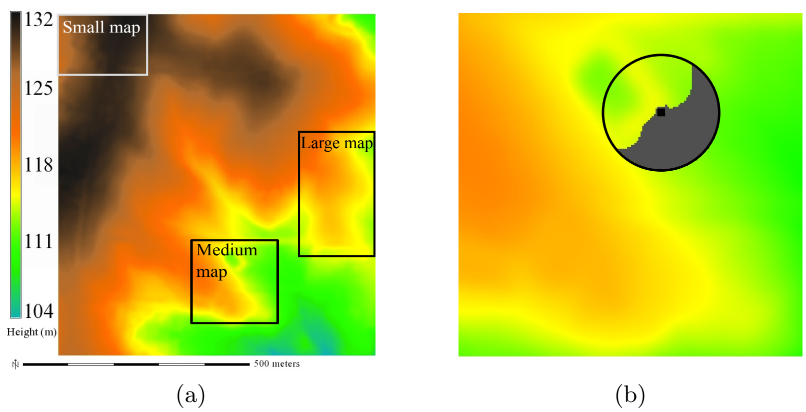


Fig. 2. Impact on coverage of visibility conditions for a given topographical map: (a) elevation is depicted by colour (the subsections of the environment surrounded inside the rectangles will be used in the result section to evaluate the performance of the algorithm); (b) assuming that the sensor is placed in the medium map, the small black square depicts the sensor location, the grey area exposes the induced visibility mask, while the black circle represents the maximum sensing range (assuming an omnidirectional sensor).

3 Methodology

The previous problem statement suggests a straight forward evolutionary algorithm solution. We choose the Evolution Strategy (ES) paradigm and, in particular, the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) algorithm [8]. In our simulations, we attempt to gain insights into these three scenarios:

a) Deterministic deployment with 360° sensors;
b) CMA-ES deployment with 360° sensors;
c) CMA-ES deployment with 90° sensors.

For each of the three scenarios, sensors are positioned at $\tau = 1$ meter above the ground, and coverage is computed using Eq. 4. The fuzzy sets used, μ_d and μ_a, are crisp sets:

$$\mu_d(\delta) = \begin{cases} 1 & \text{if } 0 \leq \delta \leq r_s \\ 0 & \text{otherwise} \end{cases}$$

and either:

$$\mu_a(\theta) = \begin{cases} 1 & \text{if } -180 \leq \theta \leq 180 \\ 0 & \text{otherwise} \end{cases}$$

for 360° sensors, or:

$$\mu_a(\theta) = \begin{cases} 1 & \text{if } -45 \leq \theta \leq 45 \\ 0 & \text{otherwise} \end{cases}$$

for 90° sensors.

The deterministic method has been shown to achieve full coverage on the Cartesian plane [2, 9]. Fig. 3 illustrates this deployment pattern, where sensors are organized in layers of horizontal strips. Assuming sensors with sensing range r_s, they are simply distributed $\sqrt{3}\,r_s$ apart on every strip, and the strips are themselves separated from one another by $\frac{3}{2}r_s$. Furthermore, the strips are interleaved to form a triangular lattice pattern.

To conduct our experiments, we selected a mountainous area in North Carolina. The data come from a raster layer map in the "OSGeo Edu" dataset [18], that stores geo-spatial information about parts of North Carolina State, USA. More specifically, we focus on a portion of the map that covers a small watershed in a rural area near NC capital city, Raleigh. The coordinate system of the map is the NC State Plane (Lambert Conformal Conic projection), metric units and NAD83 geodetic datum. We used three portions of the map for our experiments (See Fig. 4, 5, and 6).

The full GIS data can be read using an open-source GIS software called Geographic Resources Analysis Support System (GRASS) [17], and these data provide crucial information on the terrain information of the target region (See Fig. 2). With the environmental data provided by GRASS, CMA-ES can carry out the optimization task by modifying positions and orientations of deployed sensors. CMA-ES is implemented using Evolutionary Algorithms in Python (EAP) [5], an open source software developed at the Computer Vision and Systems Laboratory of Université Laval.

4 Results

The algorithm's parameters include the number of variables, the population size (μ), the number of offspring (λ), the mutation factor (σ), and the number of

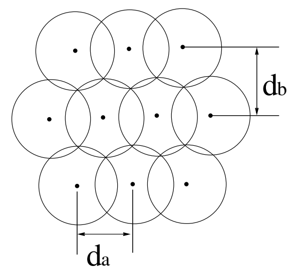


Fig. 3. Pattern of the deterministic method [2, 9] implemented in the paper, where $d_a = \sqrt{3}r_s$, $d_b = \frac{3}{2}r_s$, and r_s is the sensing range for a sensor. Circles are sensor sensing ranges, and dots are sensor positions.

Table 1. Parameters used for the CMA-ES runs

Parameter	Small map 360°	Med. map 360°	Large map 360°	Small map 90°
Dimensionality	24	32	48	144
μ	6	7	7	9
λ	13	14	15	18
σ	0.167	0.167	0.167	0.167
Generations	350	350	350	450

generations through which the algorithm runs. Tab. 1 summarizes these values. As for the sensors, we assumed that these are Passive Infrared (PIR) sensors with a sensing range of 30 meters.

We have tested the system on three different portions of the environment. While the deterministic method is supposed to achieve full coverage in each environment, the actual coverage is not even close to that figure, with less than 90% coverage in all cases. By contrast, with the same number of sensors as in the deterministic method, CMA-ES can adapt to different local elevations and thus achieve significantly better coverage (see Tab. 2).

If we add the constraint of sensing angle, the problem is even more challenging. No deterministic method has ever been proposed to solve this type of problem. However, one possible deterministic approach is to deploy four sensors instead of one sensor at the optimal positions, and each sensor will be deployed in a way that four sensors together can have an omnidirectional sensing angle. A clear drawback of this deterministic approach is that we need four times as many sensors to cover the region of interest. What is worse, the coverage is not optimal, as demonstrated before. However, an evolutionary based method such as CMA-ES again has proven its ability to deal with these problem. Using 48 sensors with 90° of sensing angle, CMA-ES demonstrates its capability to adapt to the environment and fine-tune the orientation of each sensor deployed (See Fig. 7).

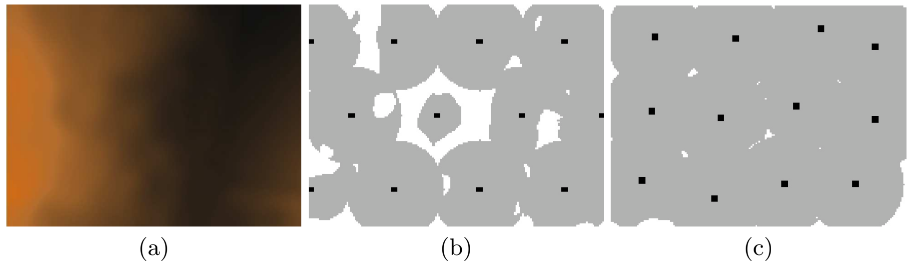


Fig. 4. Placement results on the small map: (a) two dimensional view of the environment, (b) area covered with 12 omnidirectional sensors using deterministic optimization, and (c) area covered with 12 omnidirectional sensors using CMA-ES optimization. Dark spots are sensor positions, grey areas are covered by sensors, while blank areas are uncovered. Coordinates of the environment are N: 220750, S:220615, E: 638480, W: 638300, leading to a map of 135 rows and 180 columns, for the total of 24300 cells. The data (elevation of terrain) range from 123.9 m to 131.5 m.

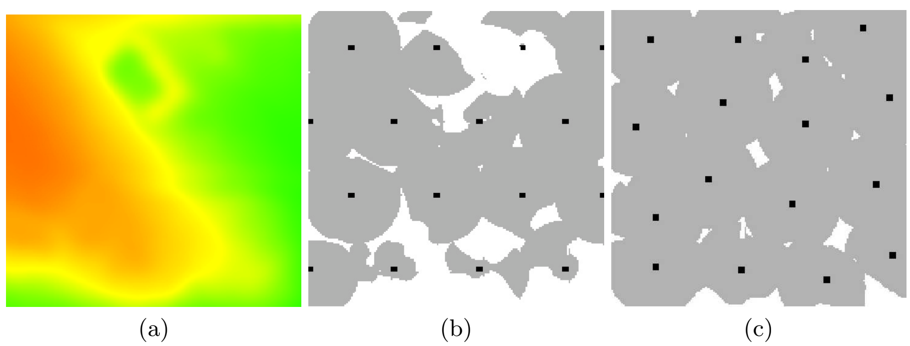
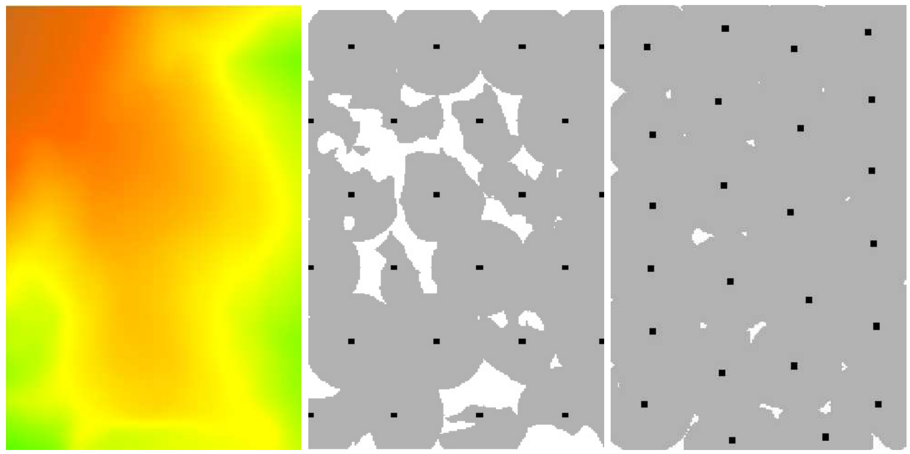


Fig. 5. Placement results on the medium map: (a) two dimensional view of the environment, (b) area covered with 16 omnidirectional sensors using deterministic optimization, and (c) area covered with 16 omnidirectional sensors using CMA-ES optimization. Dark spots are sensor positions, grey areas are covered by sensors, while blank areas are uncovered. Coordinates of the environment are N: 220250, S:220070, E: 638786, W: 638606, leading to a map of 180 rows and 180 columns, for a total of 32400 cells. The data (elevation of terrain) range from 109.7 m to 120.3 m.

CMA-ES does not only optimize sensor positions, but also sensor orientations. This capability is critical because a large proportion of existing sensors are not omnidirectional, such as vision sensors, and the need to deploy them in an efficient and optimal manner is thus of great importance.



(a) (b) (c)

Fig. 6. Placement results on the large map: (a) two dimensional view of the environment, (b) area covered with 24 omnidirectional sensors using deterministic optimization, and (c) area covered with 24 omnidirectional sensors using CMA-ES optimization. Dark spots are sensor positions, grey areas are covered by sensors, while blank areas are uncovered. Coordinates of the environment are N: 220490, S:220220, E: 639000, W: 638820, leading to a map of 270 rows and 180 columns, for a total of 32400 cells. The data (elevation of terrain) range from 111.5 m to 123.8 m.

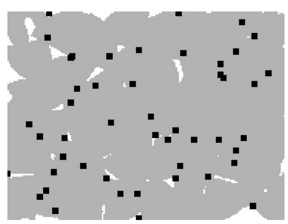


Fig. 7. Area covered by 48 sensors having a limited 90° sensing range, using CMA-ES optimization. The terrain is the small map presented in Fig. 4. Dark spots are sensor positions, grey areas are covered by sensors, while blank areas are the uncovered area.

5 Conclusion

Experimental results on topography-aware sensor deployment with CMA-ES suggest that the proposed method is fully feasible and shows good promise in optimizing sensor deployment. This project is the very first scheme to construct a realistic model for sensor deployment. To our knowledge, no similar initiatives have ever been reported in the literature.

This serves as a starting point to further investigate the use of evolutionary algorithms in sensor deployment optimization. One of our future works is to

Table 2. Coverage percentage on the target areas with various numbers of sensors and approaches. The p-value shows the probability of the CMA-ES performance being statistically similar to the deterministic one.

Method	Small map 360°	Med. map 360°	Large map 360°	Small map 90°
Deterministic	85.9%	74.3%	86.1%	–
CMA-ES run 1	98.1%	95.8%	94.5%	96.7%
CMA-ES run 2	98.9%	94.1%	98.0%	94.3%
CMA-ES run 3	95.9%	88.1%	97.1%	94.3%
CMA-ES run 4	95.7%	94.6%	97.5%	95.9%
CMA-ES run 5	98.0%	92.8%	95.2%	94.3%
CMA-ES run 6	97.8%	91.0%	97.3%	93.7%
CMA-ES run 7	95.3%	94.7%	97.9%	96.8%
CMA-ES run 8	97.6%	91.8%	97.2%	96.4%
CMA-ES run 9	97.2%	92.2%	95.6%	90.8%
CMA-ES run 10	97.4%	93.2%	96.2%	95.8%
Average	97.2%	92.8%	96.7%	94.9%
Std. dev.	1.2%	2.2%	1.2%	1.8%
p-value	$p < 0.0001$	$p < 0.0001$	$p < 0.0001$	–

implement a probabilistic or fuzzy sensing range models rather than traditional disk-like-models [2,11]. Although some probabilistic sensing range models [1,2,9, 11,21] and sensing models with irregular sensing range [4] have been proposed, without any exception they all work on a 2D flat space with omnidirectional sensors. The combinational effects of terrain variations, of constraint sensing angle or irregular sensing range, and probabilistic sensing property of sensors have never been studied. Moreover, another potential future project will be the multi-objective optimizations for sensor deployment, given the multiple concerns such as number of sensors used, energy saving, multiple coverage, and robustness of the network to sensor failures.

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