A methodology for WSN deployment in 2D large-scale constraining environments, using computational geometry algorithms

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ABSTRACT

In the past few years, the rapid evolution of the Wireless Sensor Networks (WSNs) made them a powerful tool for monitoring and observing the natural environment. WSNs are adopted more and more in various applications, e.g. for fire detection, geohazards monitoring or deformation detection in large scale areas. The spatial distribution of the sensors of a WSN must follow specific criteria. The equilateral triangle grid leads to the maximum coverage with the minimum number of sensors. Nevertheless, in most large-scale outdoor applications, achieving the ideal deployment geometry is hard or even impossible. In such environments the positions of the sensors have to be chosen among a list of possible points, which in most cases are randomly distributed. In order to achieve a geometry as near as possible to the theoretical optimum, the OptEval algorithm has been proposed. It makes use of the Centroidal Voronoi Tessellation (CVT). Although the case studies had the desired results, their simulation took place in the continuous space. There are cases, in which may be impossible to cover the whole area with sensors due to natural constraints (e.g. lakes, holes etc.). This paper evaluates the effectiveness of the proposed method in an area with holes. Alternative scenarios are examined, by changing the values of the parameters that affect the final result, i.e. the number of the points to be observed, the number of the available sensors and the radius of the sensors.

I. INTRODUCTION

Wireless Sensor Networks have rapidly evolved to a powerful tool for the monitoring and the observation of natural environment, among other fields. The early warning systems e.g. for fire or deformation detection are of the main fields that use this technology as well as the monitoring of other environmental parameters as temperature, humidity, pollution and radiation.

Determining the ideal position of each sensor of the network is of crucial importance in terms of both geographical and network coverage.

The geographical planning of a WSN must follow a simple rule: Maximum coverage with the minimum number of sensors. The key to achieve this, is the ideal geometry. That is to place the sensors (nodes) in the equilateral grid positions. Usually, this gets impossible to be achieved. Either because the number of the sensors is extremely big and the deployment in such geometry would raise the network deployment cost or because the application itself determines that the nodes position can only be chosen among a set of predetermined positions.

Additionally, in many real-life applications it may be impossible to cover the whole area with sensors due to natural constraints (e.g. lakes, holes, buffer zones etc.)

A common such as land slide detection projects, some thousands of sensors are needed. The placement of the sensors in equilateral grid would take too long in time. Moreover, the deployment positions are distributed in random positions inside the area.

The optimum solution for the coverage problem of WSN nodes is the main requested by the scientific community. Computational geometry seems to be ideal for solving the multi-criteria problem of network coverage, as many solutions are based to its algorithms and applications.

Whichever algorithm is chosen, the user wants to know a priori how well does the deployment plan approximates the ideal geometry. A geometry as near as possible to the ideal one, minimizes the numbers of sensors needed, which leads to less costs for the entire network.

A geometrical approach to the deployment problem using Centroidal Voronoi Tessellation (CVT) was proposed by (Iliodromitis, 2017). The OptEval algorithm, using the Centroidal Voronoi Tessellation (CVT), results in the nearest possible geometry to the ideal one, minimizing the numbers of sensors needed, which subsequently means lower cost for the entire network.

This paper examines the proposed method in different scenarios for the same area with randomly distributed observation points and four holes inside it. The different parameters that affect the final result, such as the number of observation points, the number of the available sensors and the number of iterations of the Lloyd's algorithm, are changed.

The rest of this paper is organized as follows: In Section II, previous work related to the deployment and the evaluation of area coverage methods are described. In section III, the deployment and evaluation methodologies are explained briefly. In section IV, the case study with 90 different scenarios, according to the different parameters, is described, as well as the outcome. Finally, Section V concludes the paper.

II. Related Work

The scientific community has been occupied to a significant extent with finding the optimum solution for the coverage problem of WSN nodes.

Computational geometry seems to be ideal for solving the multi-criteria problem of network coverage, as many other solutions are based to its algorithms and applications.

In most papers, only a couple of scenarios are described for each method, so it is difficult to understand and explain the reaction of each algorithm towards the change of the different parameters.

Additionally, there is a complete lack of papers, testing the proposed algorithms in areas with physical constraints, as described above (buffer zones, holes, sub-areas that are not needed to be observed etc).

There is a main constraint that the solution must follow. The sensors have to be deployed in certain positions chosen from a list of possible ones. The methodology tested in this paper is explained thoroughly by (Iliodromitis, Pantazis, Vescoukis, 2017), and tested by (Iliodromitis, Lambrou, 2018).

It was the first time the coverage problem was approached using this part of computational geometry, although the same method was proposed by (Zhou, Jin & Wu, 2013) for optimizing the network communication problem.

Voronoi Diagram (VD) is proposed as an approach to the solution by (Vieira et al, 2003) but for a large number of sensors the algorithm becomes extremely time consuming.

Delaunay Triangulation (DT) is the basis for coverage algorithms. A methodology to minimize energy consumption and achieve complete coverage of the area is proposed by (Wang and Medidi, 2007), but they study the ideal geometry scenario with no constraints. The aforementioned algorithm is improved by (Vu and Li, 2009) studying the boundary effect, but they mainly focus on minimizing energy consumption. Another coverage proposal using DT is set by (Wu, Lee, & Chung, 2006). A solution using Delaunay Triangulation with constraints (CDT) is proposed by (Devaraj, 2015).

Another study has been conducted by (Argany et al, 2011). They gather and record different coverage algorithms for WSN. They focus on algorithms based on DT and VD, and propose a solution that uses Voronoi polygons based on spatial information (physical boundaries, DTM etc).

However, there are additional constraint that has to be examined. There may be sub-areas that the sensors can't be deployed (e.g. a lake inside the area) or in some sub-areas we may be not interested to deployed.

Apart from the lack of different scenarios, one can note the lack of an evaluation index to verify how good or how efficient the deployment is. Most of the indexes proposed compare the deployment method with other deployment methods, without providing a universal value for the spatial distribution of the sensors of a WSN.

A typical index is proposed by (Chizari, Hosseini, & Poston, 2011). They determine the percentage of the area covered by at least one sensor in relation to the whole area and the distances between the sensors. Furthermore, the sensors are separated in those that have large, adequate or small number of other sensors near them. The percentage of the supervised area is also used as an index by (Vieira, et al, 2003). In both cases no information is given for the sub-areas that are not covered by any sensor or how well the deployment of the sensors approximates the ideal triangular grid, which results in the optimum area coverage.

An appropriate index is proposed by (Iiodromitis, 2017) and explained by (Iliodromitis, Pantazis, Vescoukis, 2017). The "g" index evaluates the geometry achieved in a WSN based on Delaunay Triangulation. The deployment positions are modeled as a Delaunay Triangulation and all scenarios are compared to the equilateral triangle grid. The proposed methodology is easy to be programmed as it is based on tools and methods of computational geometry. The index takes into account the geometry of triangles that are formed from the deployment positions. It is independent of the position or the orientation of the triangles.

Furthermore, it allows to compare the triangles meshes created in scenarios with different sensing range. The metric is unique for each scenario, so the different scenarios are directly comparable.

III. The Deployment and Evaluation Methodologies

A. *The deployment method*

A CVT is a special Voronoi Diagram, where the generating point of each Voronoi cell is also its mean (i.e., center of mass) (Zhou, Jin, Wu, 2013). In other words, the generator of each CVT polygon must also be the centroid of each polygon. It approximates an ideal partition of the area, through the optimal allocation of the generators. According to Gersho's conjecture, "as the number of generators increases, the optimum CVT will form a uniform partitioning of the space, with shapes that would result from the repetition of a single polytope. The shape of the polytope only depends on the spatial dimension". In 2D the basic polygon is a regular hexagon (Du, Wang, 2005).

In limited field applications where the sensors to be deployed are few, the deployment can be done to the positions arising after the CVT construction. These positions are the center of mass of the polygons and they do not refer to specific points of the original dataset. There are cases that the deployment positions must belong to the original set. Therefore, result additional constraints.

The solution is approached in two phases:

Given the coordinates of the points to be observed (which are the candidate deployment positions, simultaneously), the convex hull is determined (de Berg et al., 2008), (Joswig, Theobald, 1998). Then according to the number of sensors, the sensing range and the termination condition for the Lloyd's algorithm the theoretical positions of the sensors are determined, i.e. the CVT generators.

Finally, the actual deployment positions are determined, by finding the nearest neighbors that belong to the original dataset and moving the theoretical points to the closest real position.

B. *The Evaluation Method*

The fact that the equilateral triangle consists of three edges equal, leads to a specific property, using measures of dispersion from the science of statistics (Bolstad, 2007). The standard deviation of the mean of its edges, is equal to zero. The smaller the standard deviation is, the closer the random triangle is to the equilateral one.

The use of the mean value $\bar{\sigma}_0$ of the standard deviations of the edges of each triangle of the TIN, shows how well the triangles that are formed adapt to the regular triangular grid.

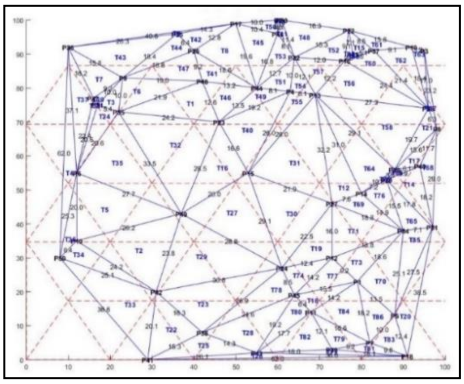

Figure 1. Comparison of vertexes of a TIN vs equilateral triangle grid

When the number of the triangles is increased or decreased (e.g. when the number of sensors changes), the index changes and the results are directly comparable. The problem arises when comparing scenarios involving sensors with a different sensing range R. Then, in these cases the index to be used will be:

$$g = \frac{\bar{\sigma}_0}{R} \tag{1}$$

The smaller prices the index gets, the better adjustment is achieved.

For the final positions of the sensors, the corresponding Delaunay Triangulation is constructed (Devadoss and O Rourke, 2011), choosing the appropriate algorithm (Cormen et al, 2009), (de Oliveira, 2012) and the TIN is compared with the equilateral triangle grid.

IV. Case Study

In order to examine the operation and efficiency of the above procedures in areas with constraints, different scenarios were created and tests were performed with different parameters.

Scenarios included different number of points for observation, different number of sensors and various sensing ranges Rs in order to find if the solutions follow specific patterns and compare them.

The dataset that is used consists of randomly generated points.

An area of 1000m x 1000m (fig. 2) was chosen with 4 empty sub-areas in it. In these 4 areas is considered that no sensor deployment can be done. The total area excluding the empty sub-areas is 770000m^2.

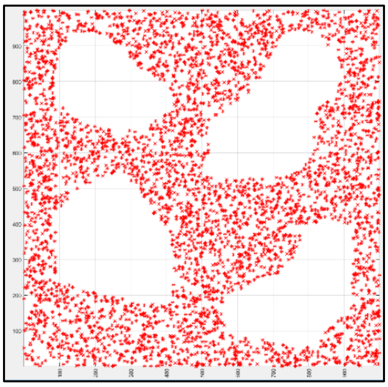

Figure 2. The case study area

Three basic scenarios were created concerning three different types of observation point densities: low medium and high. For each case 3 different range sensors (20m, 30m and 40m) were used.

Taking in to consideration the sensor range, the minimum number of required sensor comes out as the ratio of the examined area (for this case 770000m^2) to the area that every sensor covers. For the range of 20m the denominator is equal to 1256m^2 namely min 610 sensors, for the range of 30m is equal to 2827m^2 namely min 270 sensors and for the range of 40m is equal to 5026m^2 namely min 150 sensors.

Finally, for each one of the different cases, the coverage of the area was examined for a different number of sensors (10 different cases). Starting from the minimum number of required sensors and gradually increasing their number, up to about 50% more. The 90 different scenarios are presented in Figure 3.

For each case, the number of points not observed by any sensor and the coverage percentage of the points, the standard deviation of the mean of the triangle edges $\bar{\sigma}_0$, and the g index are recorded.

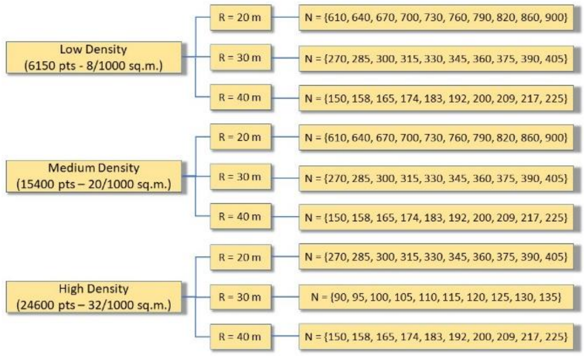

Figure 3. The different scenarios that were created

Figure 4 shows two of the created scenarios:

- Low density, R = 30m and N = 315 (fig. 4a)
- Medium density, R = 40m and N = 183 (fig. 4b)

The coverage percentages are 95.79% (182 unsupervised points) and 96.73% (437 unsupervised points) respectively.

Unsupervised points are depicted in red colour and are concentrated mainly near or on the internal and external boundaries of the area, while very few are within the area.

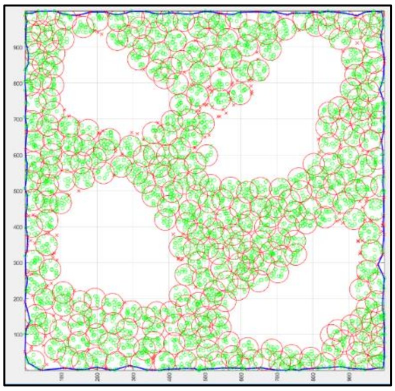

Figure 4a. Sensor deployment for low density, R=30m and N=315

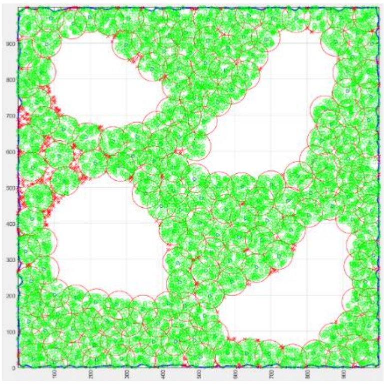

Figure 4b. Sensor deployment for medium density, R=40m and N=183

Figure 5 shows the coverage percentage achieved in relation to the number of sensors used for the three different densities and the three different ranges.

In all cases examined, even if the minimum number of sensors is used, coverage percentage of 88% - 90% is achieved. On the other hand, no full coverage is achieved even if 50% more sensors than the minimum are used. The maximum coverage achieved is about 99% which is assessed as satisfying. Most unsupervised points are concentrated to the inner and outer boundaries of the area.

An important outcome is about the influence of the increment of the number of sensors to the coverage percentage. Increasing the number of the sensors over a number does not means significant increase of the coverage percentage. Thus, the cost of the network deployment increases without improving the desired solution significantly.

The decision that has to be taken is, if the increase of the number of the sensors, has the desired impact on the coverage percentage of the network. This mainly depends on the needs of each application and the cost of the additional number of sensors in the total cost of the network. In any case, if a small subarea with points remains unsupervised due to its geometry can be treated autonomously and the sensors can be deployed manually.

Moreover, the most effective sensor in terms of the coverage percentage is the one with the larger radius R. For the same number of sensors, the coverage percentage in the different densities (low, medium and high) is less varied than the other two types of sensors. Therefore, it could be used in are-as with unequal point density, without having to separate it into individual sections, for which a separate case study should be done.

The sensing range does not affect the coverage percentage achieved. The same percentage increase of the number of the sensors, leads to a similar increase in coverage percentage.

Nevertheless, the most effective sensor in terms of the coverage percentage in the three basic scenarios is the one with the larger radius. For the same number of sensors, the coverage percentage in the different densities (low, medium and high) is less varied than the other two types of sensors. Therefore, it could be used in areas with unequal point density, without having to separate it into individual sections, for which a separate case study should be done.

The empty sub-areas do not affect the coverage percentage as this remains as high as the continuous area (Iliodromitis, Lambrou, 2018).

Figure 6 shows the change of the g index for each scenario. The g index values fluctuate from 0.24 to 0.47 for all the scenarios.

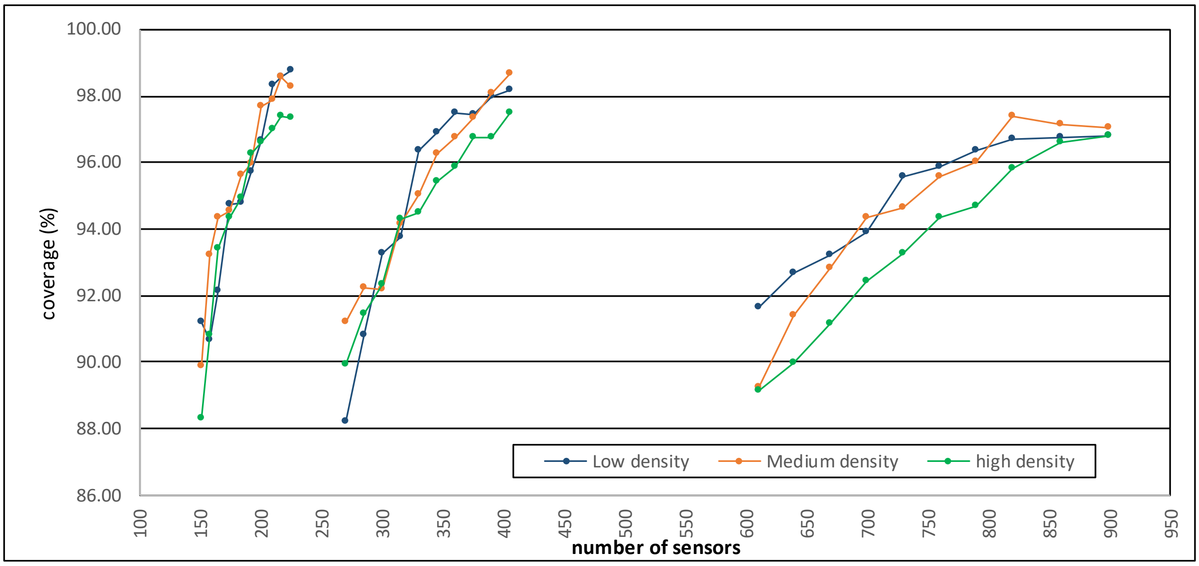

Figure 5. Coverage percentage achieved in relation to different density areas the number of sensors used for different R

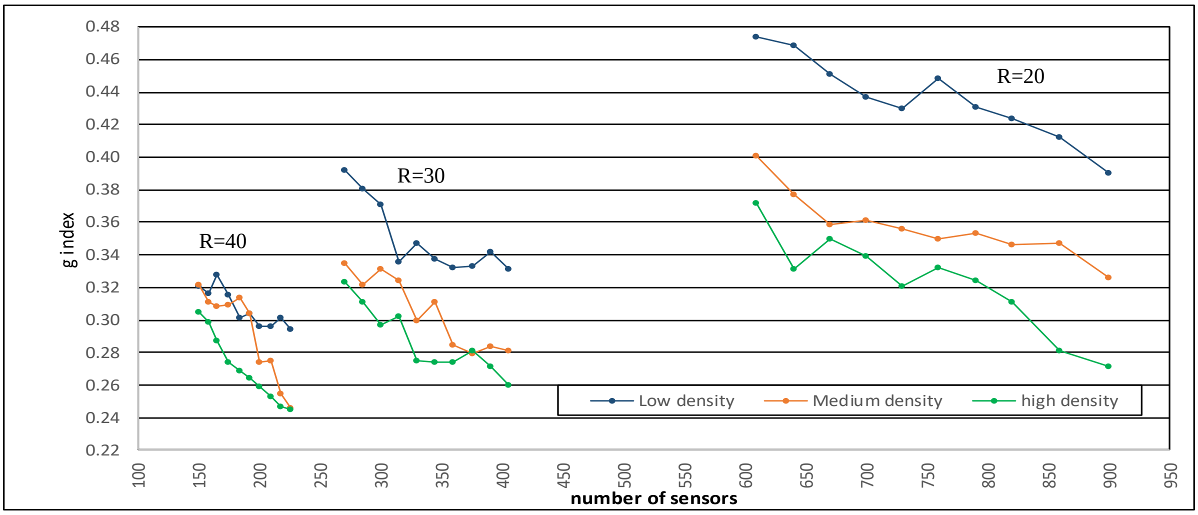

Figure 6. The change of the g index in comparison to the number of the sensors for each scenario

There is a constraint at the evaluation process of the network. The internal empty sub-areas must be excluded from the TIN creation. Otherwise there will be triangles with big and uneven edges, leading to false calculation for the g index (fig. 7b).

Thus, breaklines were formed at the internal boundaries and the Delaunay Triangulation was created only for the supervised area (fig 7a).

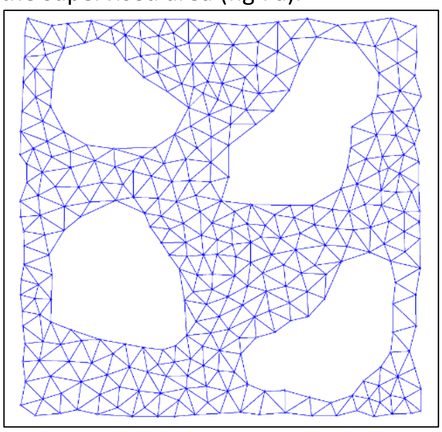

Figure 7a. Delaunay Triangulation using breaklines

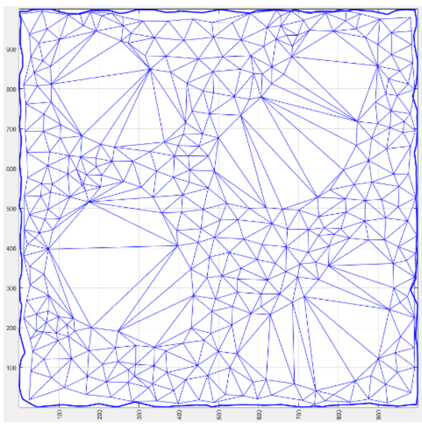

Figure 7b. Delaunay Triangulation without using breaklines

Using sensors with higher radius, the g index get lower values, meaning that the quality of the deployment is better. The range of g for the 40m sensors is less than 0.1. The corresponding value for the 20m and 30m sensors is about 0.2.

That means that for longer range sensors, the network tends to form geometry closer to equilateral grid. In order to achieve the same quality deployment as this of 40 sensors we need double sensors of 30m and six times more sensors of 20m.

Moreover when the number of sensors increase, the g index decreases. Therefore the better adjustment is achieved. As the density of points in the area increases, the g index decreases.

Both conclusions were also verified in previous work concerning a continuoys area (Iliodromitis, Lambrou, 2018).

The g index gets bigger values than these, in an area with no internal holes, but it follows a similar pattern, comparing the corresponding diagrams.

V. Conclusions

Wireless Sensor Networks are increasingly used to support a wide variety of applications, such as environmental or structural monitoring. In all cases, maximum geographical coverage with the minimum number of sensors is required.

OptEval algorithm offers a geometrical solution to the problem, based on the properties of Centroidal Voronoi Tessellation. This ensures that the solution given is the best for the given geometry (points' distribution, number of sensors, sensing range). Each sensor is placed as far away as possible from its neighbors.

A total of 90 different scenarios have been carried out for an area with specific dimensions and four internal holes inside it. Different points' density, number of sensors and sensor radii were tested.

The simulations showed that the algorithm is efficient for such areas too. The coverage percentage is about the same as in a continuoys coverage area with similar characteristics. In both cases it varies from 88% to 98%.

The analysis of the results shows that increasing the number of the sensors above a threshold does not lead to a significant increase in coverage percentage.

The g index is an index which takes into account the geometry of triangles that are formed from the deployment positions. The metric is unique for each scenario, so different scenarios can directly be compared.

The use of breaklines along the internal boundaries was critical for the calculation of the index. Breaklines prevent undesirable triangles to be created during TIN formation, which would lead to false calculation of the index.

The results of the index are similar to the continuous coverage area too. The g index gets bigger values than these, in an area with no internal holes, but it follows a similar pattern, comparing the corresponding diagrams.

Increasing the number of the sensors results in a reduction of the g index, which implies that the random triangle mesh is adjusted better to the equatorial triangle grid.

For future work concave polygons and polygons buffer zones will be examined.

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