Development of a GIS-Based Method for Sensor Network Deployment and Coverage Optimization

Thèse

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Résumé

Au cours des dernières années, les réseaux de capteurs ont été de plus en plus utilisés dans différents contextes d'application allant de la surveillance de l'environnement au suivi des objets en mouvement, au développement des villes intelligentes et aux systèmes de transport intelligent, etc. Un réseau de capteurs est généralement constitué de nombreux dispositifs sans fil déployés dans une région d'intérêt. Une question fondamentale dans un réseau de capteurs est l'optimisation de sa couverture spatiale. La complexité de l'environnement de détection avec la présence de divers obstacles empêche la couverture optimale de plusieurs zones. Par conséquent, la position du capteur affecte la façon dont une région est couverte ainsi que le coût de construction du réseau.

Pour un déploiement efficace d'un réseau de capteurs, plusieurs algorithmes d'optimisation ont été développés et appliqués au cours des dernières années. La plupart de ces algorithmes reposent souvent sur des modèles de capteurs et de réseaux simplifiés. En outre, ils ne considèrent pas certaines informations spatiales de l'environnement comme les modèles numériques de terrain, les infrastructures construites humaines et la présence de divers obstacles dans le processus d'optimisation.

L'objectif global de cette thèse est d'améliorer les processus de déploiement des capteurs en intégrant des informations et des connaissances géospatiales dans les algorithmes d'optimisation. Pour ce faire, trois objectifs spécifiques sont définis. Tout d'abord, un cadre conceptuel est développé pour l'intégration de l'information contextuelle dans les processus de déploiement des réseaux de capteurs. Ensuite, sur la base du cadre proposé, un algorithme d'optimisation sensible au contexte local est développé. L'approche élargie est un algorithme local générique pour le déploiement du capteur qui a la capacité de prendre en considération de l'information spatiale, temporelle et thématique dans différents contextes d'applications. Ensuite, l'analyse de l'évaluation de la précision et de la propagation d'erreurs est effectuée afin de déterminer l'impact de l'exactitude des informations contextuelles sur la méthode d'optimisation du réseau de capteurs proposée.

Dans cette thèse, l'information contextuelle a été intégrée aux méthodes d'optimisation locales pour le déploiement de réseaux de capteurs. L'algorithme développé est basé sur le diagramme de Voronoï pour la modélisation et la représentation de la structure géométrique des réseaux de capteurs. Dans l'approche proposée, les capteurs change leur emplacement en fonction des informations contextuelles locales (l'environnement physique, les informations de réseau et les caractéristiques des capteurs) visant à améliorer la couverture du réseau. La méthode proposée est implémentée dans MATLAB et est testée avec plusieurs jeux de données obtenus à partir des bases de données spatiales de la ville de Québec. Les résultats obtenus à partir de différentes études de cas montrent l'efficacité de notre approche.

Abstract

In recent years, sensor networks have been increasingly used for different applications ranging from environmental monitoring, tracking of moving objects, development of smart cities and smart transportation system, etc. A sensor network usually consists of numerous wireless devices deployed in a region of interest. A fundamental issue in a sensor network is the optimization of its spatial coverage. The complexity of the sensing environment with the presence of diverse obstacles results in several uncovered areas. Consequently, sensor placement affects how well a region is covered by sensors as well as the cost for constructing the network. For efficient deployment of a sensor network, several optimization algorithms are developed and applied in recent years. Most of these algorithms often rely on oversimplified sensor and network models. In addition, they do not consider spatial environmental information such as terrain models, human built infrastructures, and the presence of diverse obstacles in the optimization process.

The global objective of this thesis is to improve sensor deployment processes by integrating geospatial information and knowledge in optimization algorithms. To achieve this objective three specific objectives are defined. First, a conceptual framework is developed for the integration of contextual information in sensor network deployment processes. Then, a local context-aware optimization algorithm is developed based on the proposed framework. The extended approach is a generic local algorithm for sensor deployment, which accepts spatial, temporal, and thematic contextual information in different situations. Next, an accuracy assessment and error propagation analysis is conducted to determine the impact of the accuracy of contextual information on the proposed sensor network optimization method.

In this thesis, the contextual information has been integrated in to the local optimization methods for sensor network deployment. The extended algorithm is developed based on point Voronoi diagram in order to represent geometrical structure of sensor networks. In the proposed approach sensors change their location based on local contextual information (physical environment, network information and sensor characteristics) aiming to enhance the network coverage. The proposed method is implemented in MATLAB and tested with several data sets obtained from Quebec City spatial database. Obtained results from different case studies show the effectiveness of our approach.

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Acronym

2D	Two-Dimensional
3D	Three-Dimensional
ANOVA	Analysis of Variance
API	Application Programming Interface
CEN	European Committee for Standardization (French: Comité Européen de Normalisation)
CI	Contextual Information
CityGML	City Geography Markup Language
CMA	Covariance Matrix Adaptation
CMA-ES	Covariance Matrix Adaptation Evolution Strategy
CRG	Center for Research in Geomatics
DRDC	Defence Research and Development Canada
DSM	Digital Surface Model
DT	Delaunay Triangulation
DTM	Digital Terrain Model
EA	Evolutionary Algorithm
FGDC	Federal Geographic Data Committee
GA	Genetic Algorithm
GEOIDE	GEOmatics for Information Decisions (a Scientific Network)
GIS	Geographic Information System
GPS	Global Positioning System
GSN	GeoSensor Network
IEEE	Institute of Electrical and Electronics Engineers
ISO	International Organization for Standardization
LOD	Level Of Detail
LVSN	Computer Vision and Systems Laboratory (French: Laboratoire de Vision et Systèmes Numérique)
MDA	MacDonalds, Dettwiler and Associates (a Canadian Aerospace, GIS, and Robotics Company)

MEMS	MicroElectroMechanical Sensor
OGC	Open Geospatial Consortium
SA	Simulated Annealing
TIN	Triangulated Irregular Network
UML	Unified Modeling Language
VD	Voronoi Diagram
VEC	VECtor-based algorithm
VOR	VORonoi-based algorithm
WSN	Wireless Sensor Network

To my family,

And those who are pushing science boundaries…

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Foreword

This thesis has been prepared as an article insertion thesis and includes three international scientific journal papers and one international conference paper. The author of this thesis, Meysam Argany, is the principle author of these papers. The co-authors are Prof. Mir-Abolfazl Mostafavi, his supervisor, Dr. Christian Gagné, his co-supervisor, Dr. Farid Karimipour, Dr. Reda Yaagoubi, and Mr. Vahab Akbarzadeh. The author's contribution in these manuscripts was to perform all the experimental work, data preparation and analysis, and to write the first draft versions, which were revised by co-authors through their comments and recommendations before submission.

The papers that were inserted in this thesis are as follows:

Journal Papers:

1. Argany, M., Mostafavi, M. A., Karimipour, F., & Gagné, C. (2011). A GIS Based Wireless Sensor Network Coverage Estimation and Optimization: A Voronoi Approach. Transaction on Computational Science XIV, 6970, 151–172.

2. Argany, M., Mostafavi, M.A., Gagné, C. (2014). Context-Aware Local Optimization of Sensor Network Deployment. Journal of Sensor and Actuator Networks (JSAN), Submitted.

3. Argany, M., Mostafavi, M. A., Akbarzadeh, V., Gagne, C., & Yaagoubi, R. (2012). Impact of the Quality of Spatial 3D City Models on Sensor Networks. Geomatica, 66(4), 291–305.

Conference Paper:

4. Argany, M., Mostafavi, M. A., & Karimipour, F. (2010). Voronoi-Based Approaches for Geosensor Networks Coverage Determination and Optimisation: A Survey. In 2010 International Symposium on Voronoi Diagrams in Science and Engineering (pp. 115–123). Ieee. doi:10.1109/ISVD.2010.36

The author of this thesis has had also contribution to publish a book chapter, which has been used partially in this thesis as well as a journal paper, which has not been included here.

Book Chapter:

5. Karimipour, F., Argany, M., Mostafavi, M.A. (2013) Spatial Coverage Estimation and Optimization in GeoSensor Networks Deployment. Book chapter, Wireless Sensor Networks: From Theory to Applications, Editors: El Emary, I. M. M., Ramakrishnan, S., CRC Press, Taylor and Francis, 59-83.

Journal Paper:

6. Akbarzadeh, V., Gagne, C., Parizeau, M., Argany, M., & Mostafavi, M. A. (2013). Probabilistic Sensing Model for Sensor Placement Optimization Based on Line-of-Sight Coverage. IEEE Transactions on Instrumentation and Measurement, 62(2), 293–303. doi:10.1109/TIM.2012.2214952

CHAPTER 1

Introduction

1.1 Research Context

The importance of monitoring, collecting, and distributing location based information on diversed dynamic phenomena has been highlighted in different applications. Sensor networks are widely used for collecting information needed to establish smart environments, smart buildings, utilities, industries, home, shipboard, transportation systems, or elsewhere. Sensor networks are also useful in vehicle traffic monitoring and control. Most traffic intersections have either overhead or buried sensors to detect vehicles and control traffic lights. Furthermore, video cameras are frequently used to monitor road segments with heavy traffic, with the video sent to human operators at central locations (Chong & Kumar 2003). Sensor networks can be used for infrastructure security in critical buildings and facilities, such as power plants and communication centers. Networks of video, acoustic, and other sensors provide early detection of possible threats (Soro & Heinzelman 2005). Commercial industries has long been interested in sensing as a means of lowering cost and improving machine (and perhaps user) performance and maintainability. Monitoring machine "health" through determination of vibration or wear and lubrication levels, and the insertion of sensors into regions inaccessible by humans, are other examples of industrial applications of sensors (Chong & Kumar 2003). A broad classification of sensor network applications may include the monitoring of continuous phenomena (e.g., to assess plant health and growth circumstances, or to observe and measure geophysical processes), detecting of real time events (e.g., flood and volcano), and tracking of mobile objects (e.g., animal monitoring) (Nittel 2009; Szewczyk et al. 2004; Worboys & Duckham 2006).

What is a sensor network? Sensor networks are usually composed of a set of small, smart and low-cost sensors with limited on-board processing capabilities, storage and short-range wireless communication links based on radio technology. Previously, sensor networks consisted of a small number of sensor nodes that were wired to a central processing station. However, nowadays, the focus is more on wireless, distributed, sensing nodes (Worboys & Duckham 2006). A sensor node is characterized by its sensing field, memory and battery power as well as its computation and communication capabilities. A sensor can only cover a small area. However, collaboration of a group of sensors with each other can cover a more significant sensing field and hence accomplish much larger tasks. Each element of a group of sensors can sense and collect data from the environment, apply local processing, communicate data to other sensors and perform aggregations on the observed information (Sharifzadeh & Shahabi 2004). These tiny and ingenious devices are usually deployed in a wireless network for accessing remote and inaccessible areas without a wired communication and often without even power lines. Deploying sensor networks allows coverage of inaccessible areas by minimizing the sensing costs compared to the use of separate sensors. Furthermore, the size reduction of computing and storage platforms has led to low power consumption and has enabled computational platforms that can run on battery power for extended periods of time. In addition, the advances in real-time data input and output fundamentally change data collection and information preparation by sensor networks and make it available for use directly on the web. From the computation capability viewpoint, onboard computing advances including the local data analysis, data filtering and sampling have reduced the data transmission and battery consumption.

Sensor networks are also referred to as Geosensor networks as they are intensively used to acquire spatial information (Nittel 2009). Hereafter, we will use both of the terms “sensors” and “geosensors” interchangeably. Geosensors can be deployed on the ground, in the air, under water, on bodies, in vehicles, and inside buildings.

Despite the advances in the sensor network technology, the efficiency of a sensor network for collection and communication of the information may be constrained by the limitations of sensors deployed in the network nodes. These restrictions may include sensing range, battery power, connection ability, memory, and limited computation capabilities. These limitations create challenging problems for the users of the sensor networks which has pushed researchers from different disciplines in recent years to study various problems related to the design and deployments of efficient sensor networks. Also sensor networks have some limitations in modeling, monitoring, and detecting environmental processes. Environmental elements like obstacles, which exist in both static and dynamic forms, are also important considerations in realistic sensor networks. Other examples of such elements include contextual information of the sensors environment and physical phenomena in the network. It is necessary to know how to use sensor network to detect and consider those phenomena appropriately and efficiently. For this purpose, one needs to introduce relevant models of the phenomena type, the accessibility or inaccessibility of the observation area, environmental conditions, spatial relations, information availability, etc.

Sensor placement and the impact of the quality of initial datasets used to deploy sensors in the networks are two aspects of the complexity of wireless sensor networks. Therefore, choosing the way of deploying sensors and the data accuracy needed to set up a sensor network in an optimal manner are difficult due to the abundance of available deployment algorithms as well as design of a consistent, reliable, and robust network. Thus, study of wireless sensor networks is a challenging task that requires multi-disciplinary knowledge and expertise.

Coverage and communication between sensors are two important challenges in sensor network deployment. Nodes use their sensing devices to detect events occurring in the region of interest. Each device is assumed to have a sensing range, which depends on the phenomenon being sensed and the environmental constraints. The existence of obstacles affects network coverage and may result in holes in the sensing field. Communication between nodes is equally important, because information collected from the region should be transferred directly to a processing center or via its adjacent sensor. In the latter case, each sensor needs to be aware of the position of other adjacent sensors in its proximity. Several approaches exist to detect holes and increase the coverage of sensor networks through optimizing sensor placement (Romoozi & Ebrahimpour-komleh 2010; Aziz et al. 2009; Niewiadomska-Szynkiewicz & Marks 2009; Ghosh & Das 2008; Wang et al. 2009). From a broader perspective, proposed approaches can be classified as global and local solutions. Some of the proposed algorithms from both categories use computational geometry, in particular Voronoi diagrams and Delaunay triangulation, to locally identify and deal with holes and coverage problem (Wang et al. 2006). These structures are useful for evaluating the spatial distribution of sensors in the environment.

Spatial coverage of sensor networks is much related to the spatial distribution of the sensors in the environment. The deployment optimization algorithms try to distribute sensors in the field to obtain desired coverage regarding tasks at hand. However, more investigation is needed to extend the application of these algorithms in coverage determination and optimization of more complex sensor networks, e.g., sensor networks with environmental obstacles. Since little existing research has targeted the integration of geo-spatial characteristics of the environment, development of new approaches that take into account such features of the environment (e.g., heterogeneity of the field, terrain model, man-made and natural obstacles) has a practical significance. The integration of information in the form of the terrain and other spatial information will result in more realistic models of the sensor networks and will provide more efficient methods for their deployment in a real world environment. In this context, geographical information systems can help to provide the required information (e.g., digital terrain models) or spatial analyses (e.g., visibility analysis) functionalities in order to better evaluate and optimize geosensor networks.

1.2 Problem Statement

Currently sensor networks take advantage of high technology, but as explained before many challenges exist in the field to be investigated. One of these challenges is efficient determination of sensor positions in the environment, also known as the sensor placement problem. This depends not only on the consideration of geospatial information in the optimization process but also on the impact of the quality of such information on this process. This thesis tackles general and specific sensor placement problems.

1.2.1 General Problem

Finding the best sensor locations to get desired coverage of a region of interest is an important issue in sensor network deployment. In some literatures, coverage is defined according to the visibility between the observer and the target points (De Berg et al. 2000). More specifically, in sensor networks, the coverage of a point means that the point is located in the sensing field of a sensor node. Failing this condition for some points in the region of interest will result in coverage holes. Based on the mentioned definition of coverage in sensor networks, the coverage problem basically means placing a minimum number of nodes in an environment, such that every point of interest in the sensing field is well covered (Aziz et al. 2009; Ghosh & Das 2008). Sensor placement methods mainly proposed in the literature are based on simplistic models that usually assume flat terrain without obstacles (Ahmed et al. 2005). So, the general problem, of this thesis is the lack of consideration of spatial environmental elements in the current methods of deployment optimization and hence the problem of inefficient spatial coverage of such networks.

1.2.2 Specific Problems

Considering the general problem, the specific problems that will be considered in this thesis are introduced in the following subsection.

1.2.2.1 Problem with the spatial and environmental information integration in deployment process

As mentioned before, taking into account the environmental elements of the network is an important issue in coverage estimation and optimization of sensor networks. In addition to the form and the topography of area covered by the sensor network, various obstacles may prevent the sensors from covering the whole area or allowing data communication between the sensors. To carry out a realistic sensor placement scheme, it is necessary to take into account the environmental information that affects sensor performance and network coverage. Furthermore, the spatial relations among sensors in the network and between sensors and the environmental elements define other types of information to be considered in the sensor network. We called these three aspects the Contextual Information (CI).

1.2.2.2 Problem with the local deployment optimization

Most of the optimization methods used for sensor network deployment are based on considering global information and relations that exist inside the network (Romoozi & Ebrahimpour-komleh 2010; Aziz et al. 2009; Niewiadomska-Szynkiewicz & Marks 2009; Ghosh & Das 2008; Wang et al. 2009). They mostly look for the optimum solution of the problem considering the entire network connections, coverage, and sensor configurations. Usually, global methods are more sophisticated, in terms of defining and considering all spatial relations as well as different situations of environmental elements. They often use stochastic or probabilistic methods to find the answer. Thus, they need heavy calculations and as a result high processing time and resources to solve the problem. While, in local approaches, the solution is realized step by step, looking at the problem locally inside the network. These methods look at the specific parts of the network to find the answers locally, and then move to another part for searching the next step.

1.2.2.3 Problem with uncertainty in spatial information that is used in sensor deployment process

Wireless sensor networks may not cover the study area as expected when they are deployed in the real environment because of several factors. For example, some environmental impacts exist, which may lead to non-deterministic behavior, malfunction of the sensors, or even completely bar the sensor's field of view. Accuracy of the spatial information is very important in coverage estimation in sensor networks. Hence, data quality assessment is necessary in sensor network deployment, due to the dependency of the final results to the spatial information used in the optimization process. In addition, optimization models used in the sensor networks deployment are usually simplified representation of the reality, and consequently may lead to uncertainty in the results. Thus, it is important to perform the spatial data quality assessment, and define the accuracy level, which is necessary to satisfy the objective of optimization, as well as assess the impact of probable error propagation in sensor network deployment.

1.3 Research Objectives

Sensor networks have been intensely studied by researchers in the recent years. Many research works have been done and many papers have been published, but many unknown aspects are still open to study (Nittel 2009; Ghosh & Das 2008; Wang et al. 2009; Chen & Koutsoukos 2007; Akyildiz et al. 2002; Ahmed et al. 2005; Zhu et al. 2012). In this section the general and specific objective of this thesis will be explained.

1.3.1 General Objectives

The general objective of the present thesis is to improve spatial coverage in the deployment of a sensor network. Therefore, finding the best sensor location for desired coverage in the region of interest, regarding the initial situations, is the focus of this thesis. Hence, defining a conceptual framework for sensor network deployment is an important issue of the general objective of this thesis. Another aspect of main objective is to investigate different optimization algorithms of sensor deployment and introduce an algorithm to deploy a minimum number of nodes over the network in order to maximally cover the sensing area.

1.3.2 Specific objectives

In order to achieve the general objective of this research work, we have defined our specific objectives as follows:

1.3.2.1 Defining a framework in order to integrate spatial information in sensor networks deployment algorithms

As a first specific objective, we propose a conceptual framework that defines the method allowing the integration of contextual information in the sensor network optimization process. This information should include spatial information, the topography of study area as well as the natural and man-made obstacles. For that purpose, a geographic information system (GIS) is applied to model the realistic environment in a manner that more detailed environmental information is considered in the sensor network placement. Moreover, functions and capabilities available in GIS serve more spatial facilities to deploy sensors in the network. On the other hand, spatial information and geometrical relations among sensors as well as sensors and the environment need to be analyzed and investigated during the optimization process.

1.3.2.2 Developing a local context-aware optimization algorithm for sensor network deployment

Developing a local optimization algorithm according to the proposed framework for sensor network deployment is the next specific objective of the thesis to tackle the sensor placement problem, and maximize the spatial coverage of the network. In order to develop a context-aware optimization algorithm, the Contextual Information (CI) available in the network area should be investigated and considered in different spatial, temporal, and thematic cases. Hence, the concept of context needs to be defined based on its application for sensor network deployment. Then, different CI categories related to sensor networks should be introduced. They need to be considered in the optimization algorithm to make a realistic deployment through finding candidate positions of sensor nodes, which are consistent with reality. In addition, the optimization algorithm is developed to carry out the deployment regarding local configuration of sensors in the network. Thus, corresponding actions such as sensor movement inside the network are defined considering both local geometric structure of the network, and local specific CI.

1.3.2.3 To perform data quality assessment and error propagation analysis

There are many factors in a real environment that affect sensor network performance, and require investigation of data quality. It is important to determine the required level of accuracy in different applications of sensor networks as well as investigate error propagation in the mathematical equations used by the optimization algorithms. Therefore, the next specific objective of this thesis is to perform the accuracy assessment and error analysis. For this purpose, specific implications of spatial data quality criteria for a 3D city model used in sensor network optimization algorithms are investigated. Then, the impact of some data quality components (e.g. geometric accuracy, positional accuracy, etc.) on the estimation of sensor network coverage is analyzed. Afterwards, the impact of 3D city models quality on the estimation of coverage using global and local optimization algorithms is demonstrated.

1.4 Hypothesis

The general hypothesis of this research postulates that the integration of spatial and environmental information with the optimization algorithms and geometric approaches can improve sensor networks coverage and provide optimal deployment of sensor network in the real environment.

1.5 Methodology

The proposed methodology is composed of four phases to achieve the objectives of the thesis and validate the hypotheses. Given the general objective of this research, the different phases of the methodology have been defined.

1.5.1 Phase 1: Literature review

This phase was dedicated to survey the related researches and ideas, which already have been developed regarding to the sensor networks and their characteristics, specially the network coverage. This step helped in better understanding the project, its problems, objectives, available solutions and the state of the art, e.g., sensor network technology, communication in sensor networks, network topology, network control and spatial integration, data processing in sensor networks, data fusion, programming, and etc. Since the main objective of the research is coverage optimization, the literature review was classified into four categories:

1- Geosensors, sensor networks and their characteristics, challenges and current problems.

2- Coverage optimization approaches in sensor networks from global approaches, such as evolutionary algorithms to local approaches like geometric approaches, which consider the topology of the network in their algorithms.

3- The concept of context in sensor network deployment, the contextual information, different types of contextual information, and context-aware optimization methods

4- Uncertainty of geographic information, the quality of spatial data and their impact on the sensor network coverage optimization process.

The concepts related to the geographic information systems (GIS) were investigated in all parts of literature review, as it is a powerful tool to provide spatial information and spatial analysis tools for optimization process in sensor network. The literature review included both global and local optimization approaches. Then, an overview of the current and state of the art methods was done, and the appropriate techniques for applying in the context of the project was selected and introduced. Then, advantages and disadvantages of each method was discussed and the most proper way to optimize sensor placement chosen and improved.

Another important task that was explored in this phase was to find consistent and compatible datasets to make a realistic representation of the environment within GIS as an input for the sensor network optimization algorithm. The appropriate data set that has been used in this thesis is a part of down town Quebec City since it meets the requirements of applying and testing the proposed methods and algorithms. The optimization algorithms were implemented on MATLAB to carry out the experimentations and validate the proposed approaches.

1.5.2 Phase 2: To define a GIS based context-aware framework for integrating environmental information in sensor network deployment algorithms

In this phase two main ideas were pursued: defining a context-aware framework to consider the sensors, and the environmental information and explain how GIS could help to integrate the contextual information for the optimization algorithms. Given the sensor types and their characteristics, a context-aware optimization platform was developed to integrate the environmental information in order to enhance the network coverage. GIS was used in the framework to appropriately include environmental and network objects such as buildings, vegetation and sensor nodes in the framework considering different applications. Many environmental elements may be considered in the context-aware algorithms, e.g., digital terrain models (DTM) are the important issue to be explicitly included in a realistic modeling of sensor placement, which have not been considered in previous studies. In this phase of the research, we integrated spatial information in the optimization framework. Using GIS capacities improved the proposed framework ability to take into account the environmental elements in different classified layers of information such as man-made and natural obstacles, streets, building blocks, trees, poles and terrain topography as well as analyzing the information to get the intended purposes. Legal information such as restricted area for sensors deployment was introduced as another contextual information layer. Desirability of coverage in a specific area such as a distinctive street or a special building was represented as the next contextual information. These contextual information layers were supposed to be changed during the deployment optimization process. The impact of these variations on the coverage was attended in the proposed framework.

To fulfill the optimization process, all mentioned contextual information, whether environmental or network elements were applied to define logical rules in the framework. Afterward, appropriate actions are extracted using the CI, for example, to move or delete existing sensors or add new sensors in the network to satisfy the optimum coverage.

1.5.3 Phase 3: To develop a local geometric structure for network modeling and sensor placement optimization

In this phase, a sensor network was modeled using geometric approaches. This includes sensors nodes and their sensing areas as well as their topological relations within a network. Next, the optimization process was conducted using the defined structure and proposed framework. The optimization algorithm acted as an operation to rearrange node configurations in the network in order to discover the proper sensor placement aiming at desired coverage level in the network. Since, the geometric structure of sensor nodes may change during the optimization process, the coverage over the network may change as well. Therefore, the local geometric optimization algorithm was defined as an iterative method to reconstruct the geometric structure and recalculate the network coverage in each step. During running the algorithm, the coverage was compared with the former value. Then, the evolved values were accepted to conduct the new sensor actions. The optimization algorithm stopped when there was no more improvement in the new step versus the previous.

Since spatial coverage of sensor networks is related to the spatial distribution of the sensors in the environment, the algorithm applied Voronoi diagrams and the CI available in the network area. Voronoi diagrams were utilized to develop sensor deployment optimization algorithms in two categories of coverage hole detection, and healing the holes in the networks. The proposal is a generic algorithm to optimize the deployment, by means of considering the CI to determine the sensor configuration in the network. It was done through defining sensors actions such as movement, deletion, and insertion inside the network. The types of CI and their related sensor behavior might be different and customized according to the sensor network deployment task at hand. In the extended algorithm, sensors were sorted in a priority queue based on their coverage gain following related moves in the network. Then the sensor with the maximum gain was selected. The sensor obtained the highest coverage improvement by its movement in the network, and then stood at the top of the queue. By changing the position of the topmost sensor of the queue, the network configuration was updated. Next, the coverage gain of the adjacent sensors of the moved sensor was recalculated and their ordering in the priority queue was updated. In the next iteration, the (new) topmost sensor of the queue was chosen to move, and so on. This local optimization process was iteratively conducted until the predefined stopping criteria were maid. This will be explained in more details in Chapter 4.

1.5.4 Phase 4: Spatial data quality and uncertainty assessments

Spatial information is inherently uncertain. Several factors may contribute to the uncertainty of spatial information. Since spatial models are simplified representation of complex reality, they may produce and propagate errors. In addition, instruments, which are used to collect spatial information, may have some inaccuracies. The other problem that may lead to inaccuracy in data acquisition is involvement of humans in this process. The level of acceptability of the spatial data quality depends on applications (R. Devillers 2006). The quality of the spatial data may be characterized by their spatial accuracy, precision, semantic quality and their logical consistency. All of these elements of quality must be considered in order to characterize the overall quality of the spatial information.

In this phase, spatial data quality and the concept of uncertainty in spatial data were investigated with respect to the optimization of the sensor network deployment. Main criteria of spatial data quality like positional, attribute, and temporal accuracies (Oort 2006) were surveyed in this phase, and their impact on the optimization of sensor network deployment were investigated. To study the impact of uncertainty in spatial data on sensor network placement, main categories of spatial data quality assessment were tested by defining some simple analyses. The positional accuracy assessment was done by comparing with another dataset of better quality, also called "control" or "reference" data set. This comparison is absolutely relative, because it relates to the accuracy of the reference dataset (Servigne et al. 2006).

A probabilistic error model was defined based on investigating the impact of spatial data quality in sensor network deployment and sensor network coverage. After error model definition one may question how important the uncertainty in the data is. Small errors may be negligible in subsequent calculation, whereas large errors may have a significant impact. This question was answered using an error propagation model. To investigate the error propagation, one solution might be involving some deliberate errors in datasets using any above mentioned data quality criteria and study their impact on the final expected results. Consequently, a study on the accuracy and uncertainty of the different layers of spatial information, which were used to optimize the sensor network placement and its coverage, was done. For example, the accuracy assessment of obstacles, which was considered in the coverage optimization algorithm, was fulfilled. It investigated how changing the position of each obstacle will affect the coverage of deployed sensor nodes. The same procedure was done on other spatial information layers as well as the initial or final position of sensor nodes. Other components of spatial data quality may have significant impact on the sensor network optimization as well as positional accuracy.

The described methodology is illustrated in Figure 1.1.

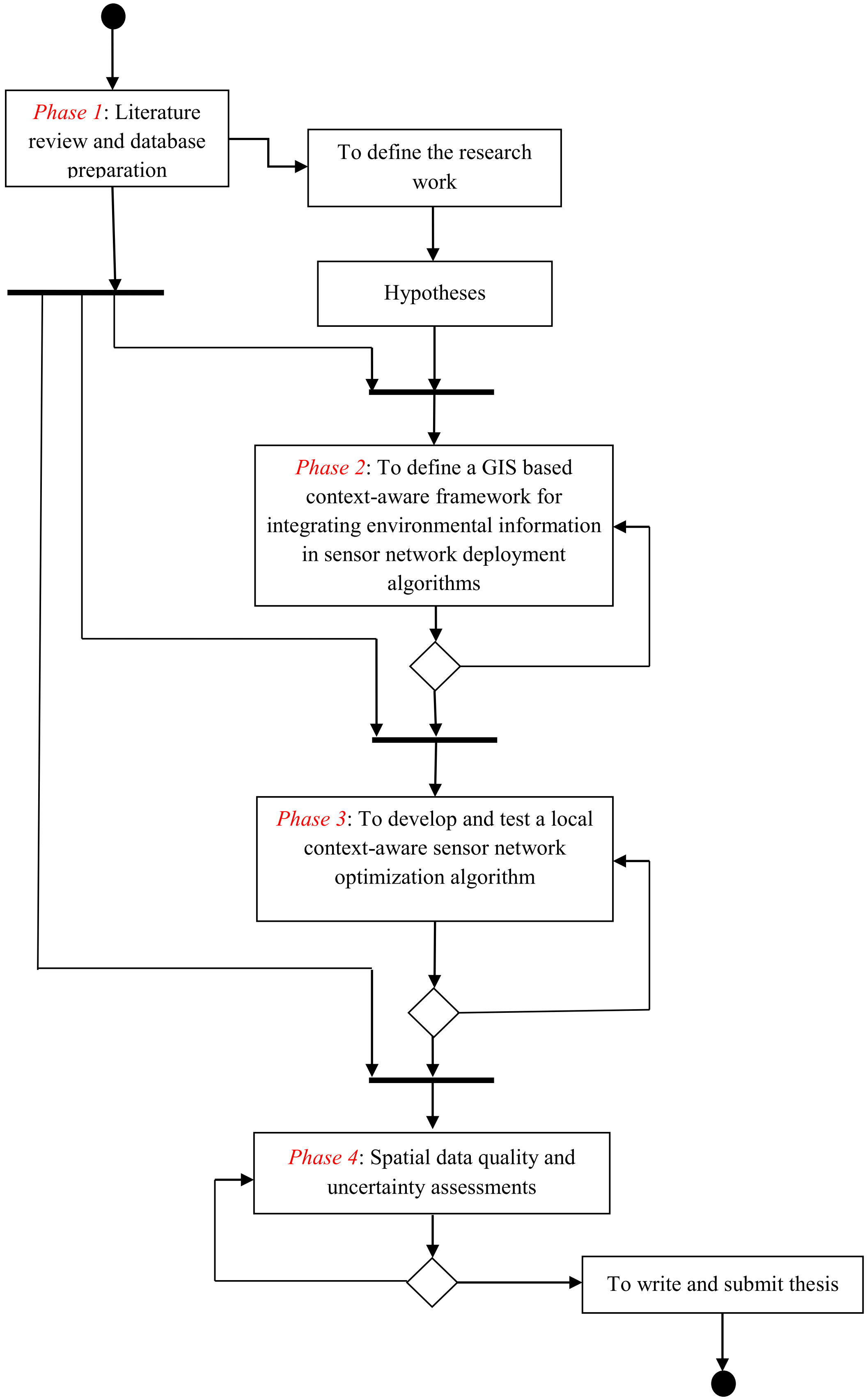

Figure 1.1: The schema of the research methodology

1.6 Organization of the Thesis

This thesis has resulted in 4 articles. Two articles that compose Chapters 3 and 5 were accepted and published in scientific journals; one that composes Chapter 2 was published as a book chapter, and one article that composes Chapter 4 was submitted to a scientific journal.

The first chapter was focused on the definition of the research context, problem statement, research objectives (general and specific), and the research method.

The second chapter presents the background of the research, including a presentation of fundamental concepts of geosensor network deployment and optimization algorithms, a review of wireless sensor network technology and applications used in this thesis, and a literature review on spatial modeling issues in sensor network deployment containing introducing the concept of optimization in sensor network deployment, which is classified in two categories of local and global optimization approaches. This chapter is published in the book entitled *Wireless Sensor Networks, From Theory to Applications* in 2013 by *Taylor& Francis, CRC Press*.

Chapters 3, 4 and 5 present the contributions of the thesis, which were submitted or published in scientific journals. The third chapter presents a GIS based wireless sensor network coverage estimation and optimization approach by using the concept of Voronoi diagram. It proposes a more realistic deployment approach by integrating spatial information in the optimization process based on Voronoi diagram and the GIS functionalities. This chapter has been published as an article in the journal of *Transactions on Computational Science XIV* in 2011.

The fourth chapter is a paper presents the context-aware optimization of sensor network deployment. This chapter proposes the problem of placing sensors in the network to get optimum coverage by investigating the concept of contextual information, and introduces a local context-aware framework of sensor network deployment optimization method. It has been submitted to the special issue "*Environmental Wireless Sensor Networks*" of the *Journal of Sensor and Actuator Networks (JSAN)*.

The fifth chapter is a paper presents the impact of the quality of a spatial 3D city model on sensor network placement optimization. It investigates specific implications of spatial data quality criteria for a dataset used in sensor network deployment optimization algorithms, and the impact of these criteria on the positions of the sensors in the network, and estimation of the network coverage. This chapter has been published as an article in the *Geomatica* journal in 2012.

The last chapter presents the conclusion of the thesis, including future research perspectives. The papers that were published and that compose the thesis have been very slightly modified after being integrated in the thesis. Consequently, the content of some chapters may seem redundant, but this is only to ensure that each article stands by its own and presents adequate background and context.

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CHAPTER 2

Fundamentals of the Geosensor Networks, Deployment, and Optimization

2.1 Introduction

Recent advances in electrical, mechanical, and communication technologies have led to development of efficient low-cost and multi-function sensors which are capable of sensing the environment, performing data processing and communicating with each other. The efficiency of sensors, in terms of data collection and communication, is constrained by limitations in sensing range, battery power, connection ability, memory, and computation capabilities. As a result, an individual sensor can sense only a small region. However, a group of sensors collaborating with each other can overcome this limitation and cover more regions of the study area. Sensors may arrange in a wireless network, each monitoring and collecting physical and environmental data such as motion, temperature, humidity, pollutants, and traffic flow for a given area. The data are then communicated to a processing center where they are aggregated and analyzed to produce desired information for different applications. Sensors are deployed randomly or based on a predefined distribution over the region of interest. They may be spread with various densities from sparse to dense distribution depending on the application as well as the type and quality of the desired information.

Efficient deployment of sensors in a wireless (geo)sensor network is an important issue that affects the coverage as well as communication between sensors. Nodes use their sensing modules to detect events occurring in the region of interest. Each sensor is assumed to have a sensing range, which may be constrained by the phenomenon being sensed, obstacles, the environment, etc. In a network of sensors, these constraints affect the coverage and may result in holes in the sensing area. Communication between the nodes is equally important. Information collected from the region covered by a sensor should be transferred to a processing center, directly or via adjacent sensors. In the latter case, each sensor must be aware of the position of other adjacent sensors in their proximity. Any failure in communication between sensors may result in holes in the aggregated information. Several optimization methods (global or local, deterministic or stochastic) have been proposed to detect and eliminate holes and hence increase the coverage of sensor networks. Some methods use general optimization techniques, whereas others consider the problem as a geometric issue and use the structures and tools of computational geometry.

This chapter presents an overview of geosensor networks and their technologies, problems, and technical challenges. It also provides a survey on the main methods proposed for estimation and optimization of spatial coverage of sensor networks, with a special focus on the geometrical methods. Sections 2.2, 2.3, and 2.4 present the state of the art on sensor networks and their related issues in terms of phenomena, type of the environment and sensor as well as issues such as coverage, communication and energy saving problems. Section 2.5 is focused on spatial and geometrical issues in the deployment of sensor networks. It describes the concepts of sensing and communication models as well as sensor network topologies. Some preliminary geometric definitions are provided at the end of this section. In Section 2.6, the spatial coverage problem is discussed in more details and a general review of optimization algorithms in geosensor network deployment is presented in Section 2.7. Later in that section, global and local approaches for sensor deployment optimization are addressed. Finally, Section 2.8 concludes the chapter and introduces some research perspectives in the field.

2.2 Wireless GeoSensor Networks: An Overview

Sensor networks are usually composed of a set of small, smart, and low-cost sensors with limited on-board processing capabilities, storage, and short-range wireless communication links based on radio technology. Previously, sensor networks consisted of small number of sensor nodes that were wired to a central processing station. However, nowadays, the sensing nodes could be wireless. The sensing field, memory and battery power, and the computation and communication capabilities characterize a sensor node. A sensor can only cover a small area. However, collaboration of a group of sensors with each other can cover a more significant sensing field and hence accomplish much larger tasks. Each element of a group of sensors can sense and collect data from the environment, apply local processing, communicate it to other sensors and perform aggregations on the observed information.

A broad classification of geosensor network applications includes monitoring continuous phenomena (e.g., to assess plant health and growth circumstances, to observe and measure geophysical processes, etc.), detecting real time events (e.g., flood and volcano), and tracking objects (e.g., animal monitoring) (Szewczyk et al. 2004; Worboys & Duckham 2006; Nittel 2009). Sensor networks have several applications including environmental monitoring, change detection, traffic monitoring, border security, public security, etc. They are used for collecting the information needed by smart environments, quickly and easily, whether in buildings, utilities, industries, home, shipboard, transportation systems automation, elsewhere. Sensor networks are useful in vehicle traffic monitoring and control. Most traffic intersections have either overhead or buried sensors to detect vehicles and control traffic lights. Furthermore, video cameras are frequently used to monitor road segments with heavy traffic, through the videos sent to human operators at central locations (Chong & Kumar 2003). Sensor networks can be used for infrastructure security in critical buildings and facilities, such as power plants and communication centers. Networks of video, acoustic, and other sensors provide early detection of possible threats (Soro & Heinzelman 2005). Commercial industries have long been interested in sensing as a means of lowering cost and improving machine (and perhaps user) performance and maintainability.

Sensor networks may create smart environments as the next evolutionary development step in building, utilities, industrial, home, shipboard, and transportation systems automation. Like any sentient organism, the smart environment relies first and foremost on sensory data from the real world. Sensory data comes from multiple sensors of different modalities in distributed locations. The smart environment needs information about its surroundings environment as well as about its internal workings.

Some considerations are raised due to sensor network limits over the modeling, monitoring and detection of environmental issues as well as difficulties of real time monitoring and analysis of dynamic objects in the network. Examples of such issues include observations of dynamic phenomena, (e.g., air pollution) or monitoring of mobile objects (e.g., animals in a habitat). It is necessary to know how to use this technology to detect and monitor those phenomena, appropriately and efficiently. For this purpose, one needs to identify the relevant mix of hardware platforms for the phenomena type, the accessibility or inaccessibility of the observation area, hazardous environmental conditions, and power availability, etc. Due to the battery constraints, today's wireless sensor network technology can be more effective at detecting and monitoring time-limited events (e.g., earthquake tremors) instead of continuous sampling in remote areas (Nittel 2009). Data acquisition and distribution networks are two aspects of complexity of wireless sensor network. Thus, choosing the components of such systems is difficult due to abundance of available technologies as well as design of a consistent, reliable, robust overall system. Study of wireless sensor networks is a challenging task, as it requires an enormous breadth of knowledge from a great variety of disciplines.

2.3 Wireless Sensor Networks Technology

Today sensor networks exploit the functions and technologies not available a few years ago. All sensor network components including sensors, processors, and communication devices that are built and deployed in sensor networks by commercial companies such as Silicon Labs, Moog Crossbow, Newtrax, and Microstrain are now getting smaller, smarter, and cheaper. Nowadays, our daily lives are enhanced through a network of small, smart, embedded sensor nodes. These sensors contain significant computing abilities in a small package that can easily be customized to become processing nodes in a sensor network. Some sensor devices take advantage of built-in sensing capabilities, such as cameras, navigation systems, microphones, thermometers, etc. Beside these advantages, attaching powerful processors to Microelectromechanical devices (MEMS) and machines along with large databases and communication platforms have brought a new era of technologically advanced sensor networks (Gardner et al. 2001).

Today, wireless networks offer low expense and high capabilities, and based upon IEEE 802.11 standards can provide characteristics close to the wired networks. The organization has defined the IEEE 802.15 standard for personal networks with the radius of 5 to 10 m.

Networks of short-range sensors are the ideal technology to be employed in personal networks. Developing such algorithms and technologies for short-range sensors will improve the development and application of the low-cost sensor networks (Anon n.d.). Furthermore, increases in chip capacity and processor production capabilities have reduced the energy consumption for both computing and communication. Sensing, computing, and communications can now be performed on a single chip, which reduces the cost and allows deployment in ever larger numbers (Kahn et al. 1999). Looking into the future, the advances in microelectromechanical technology will produce sensors that are even more capable, smaller, smarter, cheaper, and multipurpose.

2.4 Wireless Sensor Networks Problems and Technical Challenges

Sensors networks in general pose considerable technical problems in data processing, communication, and sensor management. Because of potentially harsh, uncertain, and dynamic environments, along with constraints imposed by environmental obstacles, as well as sensor's energy and bandwidth limits, wireless ad hoc networks pose additional technical challenges in network discovery, network control and routing, collaborative information processing, querying, tasking, and network deployment.

2.4.1 Sensor Network Topology

Information about the network topology is necessary for a sensor in the network to operate properly. In order to support processing and collaboration, each node needs to know the situation and location of its neighbors. Usually, the topology of the planed network may be known a priori. For dynamic networks, the network topology has to be constructed in real time, and updated periodically as sensors fail, change positions, or new sensors are deployed (Li et al. 2013). In this case, the topology is always evolving. Then, algorithms should be provided for different fixed and mobile sensors to discover each other. If each sensor node interacts only with its neighbors, global knowledge may not be needed, but in terms of sensor network deployment it is sometimes necessary to define or recognize the global topology. In addition to knowledge of the topology, each sensor also needs to know its own location. Using the GPS for self-locating is a solution. Another means of self-locating, such as relative positioning algorithms have been provided when using GPS is not feasible or too expensive (Hightower & Borriello 2001).

2.4.2 Network Control and Connectivity

Sensor networks may be forced to change their configuration as required, and operate autonomously because of the unstable resources such as energy, bandwidth, and the processing power. In networks with no planned connectivity, connectivity must come out as needed from the algorithms and software. So, in the case of unreliable communication links, the software and system design should generate the required control on the reliability of the network. This requires research into issues such as network size or the number of links and nodes needed to provide adequate redundancy (Nittel 2009).

Deploying an adequate number of nodes in the network in order to control the network paths as well as providing the algorithms to find the right paths ensures the connectivity of the network, and its adaptation to the environment. Diffusion routing method is a way to get this purpose. This method relies upon the information at neighboring nodes (Estrin et al. 1999). Another important issue in sensor network connectivity is to investigate how system parameters such as network size and density of nodes per square meter affect the tradeoffs between latency, reliability, and energy (Nittel 2009).

2.4.3 Data Fusion and Processing in Sensor Networks

Collecting and processing information are important tasks that are carried out by the nodes in the sensor networks. Collaborative signal and information processing over a network (Bal et al. 2009) as well as distributed information fusion (Moses et al. 2006; Nakamura et al. 2007) are two research aspects on sensor networks. Important technical issues in this area include the degree of information sharing between nodes and how nodes fuse the information from other nodes. Processing data from more sensors may result in better performance but also requires more communication resources. Similarly, less information is lost when communicating information at a lower level (e.g., raw signals), but requires more bandwidth. Therefore, it is necessary to consider the multiple tradeoffs between performance and resource usage in collaborative signal and information processing in sensor networks.

Detection, tracking, and classification of targets are important applications of sensor networks (Nittel 2009). Data dependency is an important issue when multiple targets are presented in a small region. Each node must associate its measurements of the environment with individual targets. In addition, targets detected by one node have to be associated with targets detected by other nodes to avoid duplication and enable fusion. Optimal data association is computationally expensive and requires significant bandwidth for communication. Thus distributed data relationship is also a tradeoff between performance and resource usage, requiring distributed data association algorithms designed to sensor networks.

2.4.4 Sensor Network Interface and Data Query

A sensor field is like a database with many unique features. Data is dynamically collected from the environment, in opposition to being entered manually. The data is distributed across nodes, and geographically dispersed nodes in the network may be connected via unreliable links. These features make the database view more challenging, particularly over the networks with low-latency, real-time, and high-reliability requirements.

It is important that users have a simple interface to interactively manipulate and query the sensor network. The users should be able to make the commands, and get access to the information, e.g., operational priority and type of target, while hiding details about individual sensors. One challenge is to develop a language for querying and tasking, as well as a database that can be readily queried (Yao & Gehrke 2003). Other challenges include finding efficient distributed mechanisms for query and task compilation and placement, data organization, and caching.

2.4.5 Real Time Output in Sensor Networks

Technical improvement in sensor platforms for collecting, storing, processing, handling, preparing and analysis of the information has led to provide the output of sensor networks as a real time data stream. Hence, huge amount of different types of data are produced by sensor platforms and as a result the streams of data will be available to be used. Accordingly, the challenge is to develop appropriate real time data management tools for analyzing and processing the sensor network data stream. Many algorithms exist to manipulate the real time data stream (Nittel 2009), like banking transactions monitoring. Since sensor networks output data are typically geo-referenced data, the existing algorithms do not support them. Other challenge includes expanding the existing tools to rapidly process huge data stream considering their temporal and spatial characteristics.

On the other hand, wide access to the Internet and the increase in real time data streams of sensor, have created more interest to design online sensor networks. Such networks are described as the “sensor web”, which let users select appropriate data streams based on their needs, like the location, application, time, and situation (Grosky et al. 2007). Users should be able to choose among available sensors, and the types of information provided by the network. Defining an infrastructure to put sensor networks and their data stream on the web is a challenging domain, as well as preparing programming tools for online data analyzing, processing, and querying.

2.4.6 Sensor Network Deployment

The spatial locations where the sensors are supposed to be deployed in the environment can greatly influence sensing performance (e.g. sensing capability according to environmental constraints, suitability for installation), as well as operation costs (e.g. hardware, deployment, maintenance). Except for trivial cases, sensor placement is a difficult problem that requires the use of sophisticated decision support systems.

There is an important challenge in sensor networks to develop innovative sensor placement algorithms, using stochastic global optimization methods, or local geometric approaches integrating terrain information (including any human built infrastructures), as well as realistic sensor models. Novel optimization methods have to be developed for generating and selecting candidate locations on which sensors can be placed according to a wide array of sensor network application preferences. This optimization process required an important computing capability and so need to be conducted on high performance computing facilities, in order to take advantage of the computational capabilities of the new algorithms.

In this thesis, our focus is more on sensor placement in the networks. Hence, the remainder of this chapter has been dedicated to the introduction of the concepts of coverage, and sensor deployment in the networks followed by the notion of optimization and their approaches in sensor network deployment.

2.5 Spatial Modeling Issues in Deployment of Wireless Geosensor Networks

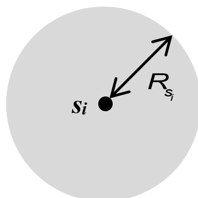
Geosensor networks can be considered as a set of points (nodes) in Euclidean space with links that present their communications. Each sensor is assigned a sensing region; and the problem is to place them such that the space is fully covered with the union of the sensing regions providing that the sensors can communicate. The key points of this definition are sensing and communication, whose modeling has a direct effect on the sensor deployment. This section presents the geometrical issues related to sensing and communication modeling. Two geometric structures, i.e., Delaunay triangulation and Voronoi diagrams, which are frequently used in the geometrical geosensor deployment strategies, are introduced at the end of this section.

2.5.1 Sensing models

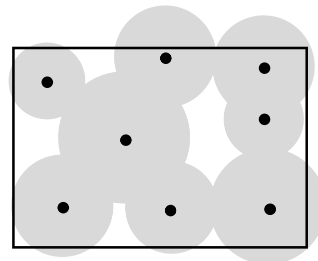
The simplest model of sensing is the binary disc model, which confines the sensibility of a sensor within a certain disk. It considers a sensing range, i.e., a circular disk of radius R_s for each sensor; Points that lie within the sensing range of a sensor are fully covered by that sensor and the points beyond it are not covered at all (Figure 2.1.a):

$$S(s_i, P) = \begin{cases} 1 & d(s_i, P) \leq R_{s_i} \\ 0 & d(s_i, P) > R_{s_i} \end{cases}$$

where *S* is the sensitivity of the sensor s_i, R_{s_i} is the radius of the disk coverage of the sensor s_i, and $d(s_i, P)$ is the Euclidean distance between sensor s_i and the point *P*. This model assumes there are no obstacles in the environment and ignores the decrease in the strength of the signal. The coverage problem of a sensor network can be simply modeled using the binary disc model through computing the union of the (not necessarily equal) sensing disks (Figure 2.1.b).



(a)



(b)

Figure 2.1: Binary disc model of sensing: (a) Only the gray region is covered by the sensor s_i; (b) Modeling the coverage problem of a sensor network using the binary disc model

To achieve more realistic extensions of this model, the following variants are applied:

- The sensibility is not binary, but varies with distance to the sensor node.
- The sensing region is not circular.

2.5.1.1 Variable sensibility

In practice, the sensing capability is not binary, but gradually attenuates with increasing distance (Figure 2.2), i.e.:

$$S(s_i, P) = f(d(s_i, P))$$

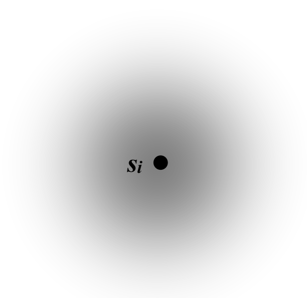


Figure 2.2: Attenuation of the sensing capacity with increasing distance to the sensor s_i

This concept is used in probabilistic sensing model to model sensitivity of devices such as infrared and ultrasound sensors (Y Zou & Chakrabarty 2004; Hossain & Biswas 2008). In this model, two quantities R_1 and R_{max} are defined, which are the starting of uncertainty in sensor detection and the maximum sensing range of the sensor, respectively. The points with a distance less than R_1 to s_i are surely covered; the points with a distance greater than R_{max} to s_i are not covered; the coverage of the points between the two above disks is a probability function of distance (Figure 2.3):

$$S(s_i, P) = \begin{cases} 1 & d(s_i, P) \le R_1 \\ f\big(d(s_i, P)\big) & R_1 < d(s_i, P) < R_{max} \\ 0 & d(s_i, P) \ge R_{max} \end{cases}$$

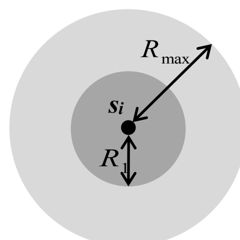


Figure 2.3: Probability sensing model: The dark gray disk is covered; the coverage of the light gray nut is a probability function of distance to s_i; elsewhere is not covered.

2.5.1.2 Non-circular sensibility

If the sensor emits signals to all directions and the environment is homogeneous, the circular sensing region fairly models the reality. However, there are cases where these assumptions are not true:

- Directional sensors, e.g., cameras, whose covered region is restricted to a certain directions (Figure 2.4) (Wang & Cao 2011a; Wang & Cao 2011b).
- In the presence of obstacles in the environment, or if the environment is not homogeneous, the sensing ability of the sensor is not uniform in all directions (Hossain & Biswas 2008).

Several modeling and strategies for coverage estimation of such cases have been proposed in the literature (Hwang & Gu 2007; Wu & Chung 2009; Yi & Guohong 2011).

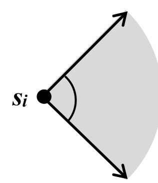


Figure 2.4: A directional sensor

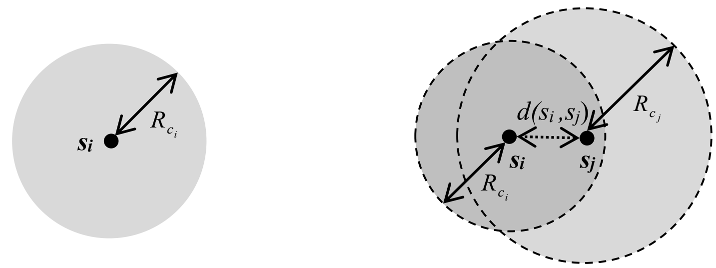
2.5.2 Communication models

Wireless sensors are small, low-power sensors with limited storage and short-range wireless communication links based on radio technology. Communication between the sensors consumes power; thus, optimizing the communications between sensors is crucial for prolonging the lifetime of wireless sensor networks (Luo & Hubaux 2005; Madan & Cui 2005; Wang & Srinivasan 2005). On the other hand, radio links between sensors are relatively unreliable, so making realistic modeling of radio communications is very challenging (Ghosh & Das 2008).

Like modeling the sensor coverage, the simplest model of sensor communication is the *binary disk model*, which assumes a communication radius R_{c_i} for each node s_i. It means that s_i is capable of communicating to sensors located up to distance R_c from it (Figure 2.5.a). However, empirical measurements have challenged this model of communication (Zuniga & Krishnamachari 2004), because in reality, the strength of radio signal emitted from the sensors attenuates with increasing distance. Furthermore, "the signal undergoes several disruptive physical phenomena, such as interference, scattering, diffraction, and reflection due to the presence of other transmissions and obstacles along its path" (Ghosh & Das 2008).

Based on the binary disk model, two nodes $s_i$and s_j can communicate with each other if the minimum of their communication radii is greater than their Euclidean distance, i.e.,

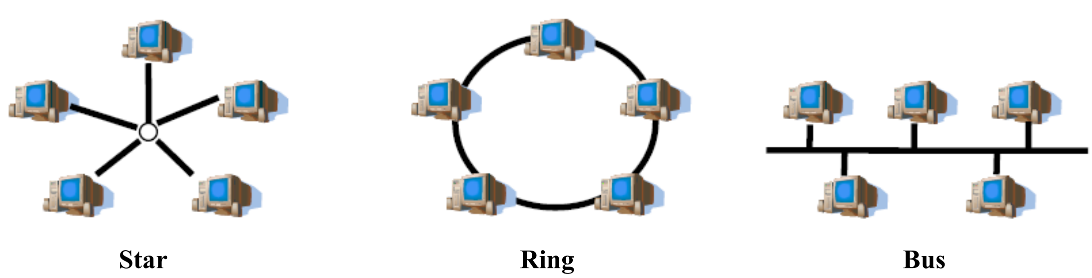
$\min\{R_{c_i}, R_{c_i}\} > d(s_i, s_j)$. It means that the sensor with smaller communication range falls in the communication range of the other sensor (Figure 2.5.b).



(a) (b)

Figure 2.5: Binary disc model of communication: (a) The sensor s_i is able to communicate with the sensors located in the gray region; (b) The sensors si and s_j can communicate with each other, because the one with the smaller communication range falls in the communication range of the other one.

Two sensors are called *one-hop neighbors* if they can directly communicate with each other. On the other hand, two sensors may not directly communicate (i.e., at least one of them does not fall in the communication range of another), but they could communicate through a sequence of intermediate sensors. Such sensors are called *multi-hop neighbors*. This idea leads to different topologies (i.e., communication strategies) in wireless sensor networks in order to maximize the life-time and communication reliability of the whole network (Salhieh & Weinmann 2001; Deb & Bhatnagar 2002; Yu & Prasanna 2005; Cao & He 2006; Muthukumar & Sureshkumar 2010). Figure 2.6 illustrates basic sensor network topologies.



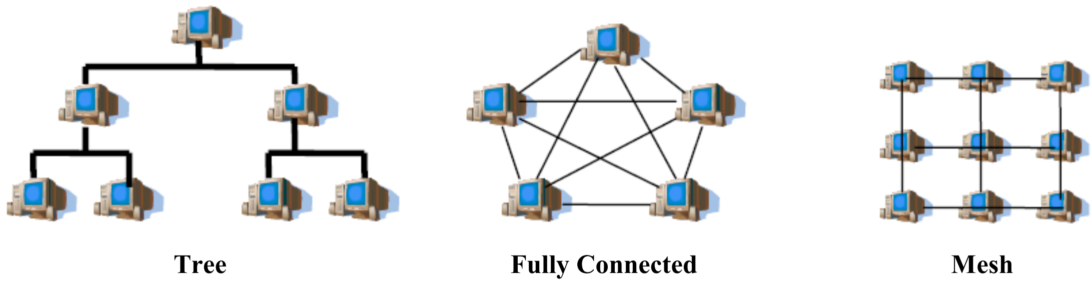


Figure 2.6: Basic sensor network topologies

The communication in wireless sensor networks is perfectly modeled using graphs: Each sensor is a node in the graph; two nodes are connected through an edge if their Euclidean distance is less than the minimum of their communication radii. Several parameters could be extracted from the induced communication graph (Ghosh & Das 2008):

- The number of one-hop neighbors of a sensor is the degree of its corresponding node in the graph.
- All sensors in the network can communicate (i.e., there is no isolated sensor) if the induced communication graph is connected. It means that there is a path between every pair of sensors. In other words, there is an edge between them (i.e., they are one-hop neighbors) or they are connected through a sequence of edges (i.e., they are multi-hop neighbors).
- The sensor network is k-node connected, if for every pair of nodes there are at least k node-disjoint paths connecting them. This parameter is an indicator of the reliability of the network.

2.5.3 Preliminary geometric structures

This subsection introduces Delaunay triangulation and Voronoi diagrams, as two geometric structures that are frequently used later in geosensor network deployment strategies.

Given a point set P in the plane, the Delaunay triangulation is a unique triangulation of the points in P, which satisfies the empty circum-circle property: the circum-circle of each triangle does not contain any other point $p \in P$ (Figure 2.7).

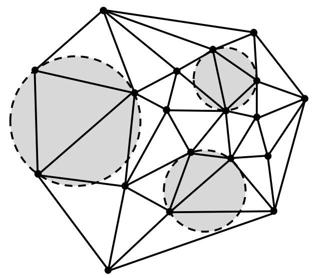


Figure 2.7: 2D Delaunay triangulations; three of the circum-circles are shown

Delaunay triangulation is the dual structure of Voronoi diagram. The Voronoi diagram (VD) of a set of points is defined as follows: Let P be a set of points in an n-dimensional Euclidean space R^n. The Voronoi cell of a point $p \in P$, noted $V_p(P)$, is the set of points $x \in R^n$ that are closer to p than to any other point in P:

$$V_p(P) = \{x \in R^n \mid \|x-p\| \leq \|x-q\|,\ q \in P,\ q \neq p\}$$

The union of the Voronoi cells of all points $p \in P$ form the Voronoi diagram of P, noted $VD(P)$:

$$VD(P) = \bigcup_{p \in P} V_p(P)$$

Figure 2.8 shows an example of a point Voronoi diagram for a set of 2D points.

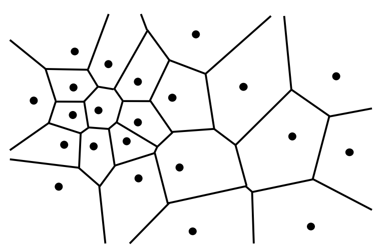


Figure 2.8: Voronoi diagram of a set of points in the plane

Delaunay triangulation and Voronoi diagram are dual structures. This means that each node in Delaunay triangulation corresponds to a Voronoi cell, each Delaunay edge corresponds to a Voronoi edge and each Delaunay triangle corresponds to a Voronoi vertex. The centers of circum-circles of Delaunay triangulation are the Voronoi vertexes; and joining the adjacent generator points in a Voronoi diagram yields their Delaunay triangulation (Figure 2.9). This duality is very useful because construction, manipulation and storage of the Voronoi diagram are more difficult than Delaunay triangulation, so all the operations can be performed on Delaunay triangulation, and the Voronoi diagram is only extracted on demand.

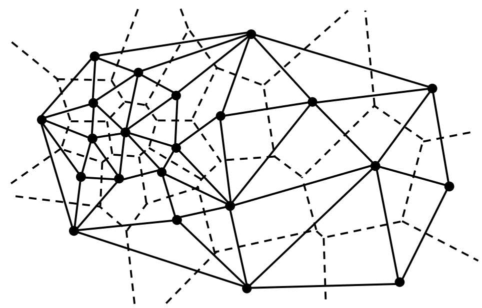


Figure 2.9: Duality of Delaunay triangulation (solid lines) and Voronoi diagram (dashed lines)

2.6 Spatial Coverage in GeoSensor Networks

In this research, the visual coverage is defined based on a direct visibility between the source and the target point. In sensor networks, however, the coverage of a point means that the point is located in the sensing range of a sensor node. As stated in Section 2.5, a uniform sensing range is represented by a disk around the sensor. Failing this condition for some points in the region of interest will result in coverage holes. Regarding the above definition of coverage in sensor networks, the coverage problem is basically placing the minimum number of nodes in an environment, such that every point in the sensing field is optimally covered regarding the initial situations (Ghosh & Das 2008; Aziz et al. 2009). Nodes can either be placed manually at predetermined locations or dropped randomly in the environment. It is difficult to find a random scattering solution that satisfies all the coverage and connectivity conditions. Thus, a deployment model must be applied to place sensors in their optimal positions or change their undesired locations.

The Voronoi diagram elegantly models the sensor coverage problem (Argany et al. 2010; Argany et al. 2011). In a Voronoi diagram, all the points within a Voronoi cell are closest to the generating node of this cell. Thus, having constructed the Voronoi diagram of the sensor nodes and overlaid the sensing regions on it (Figure 2.10), if a point of a Voronoi cell is not covered by its generating node, this point is not covered by any other sensors (X. Wang et al. 2003; Ghosh 2004; Ahmed et al. 2005; Wang et al. 2009). While computing the area of a Voronoi cell is straightforward, computing the area of the uncovered region in a Voronoi cell is a complicated task, because the sensing regions may protrude the Voronoi cells and overlay each other. Strategies for this computation are described as novel solutions in next chapters as well as the former approaches in (G. Wang et al. 2003; Ghosh 2004).

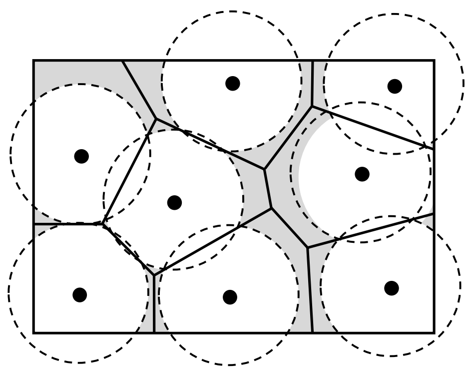


Figure 2.10: Overlaying the Voronoi diagram and sensor sensing regions to detect the coverage holes (shaded regions) in a sensor network

The estimation of coverage is defined in some literature as a measurement of the ability to detect objects within a sensor field. It is described as the expected average ability of observing a target moving in a sensor field and called coverage estimation based on the concept of exposure (Meguerdichian et al. 2001).

The so-called *worst case* and *best case* coverage are examples of methods for exposure evaluation (Meguerdichian et al. 2001; Megerian et al. 2005). Worst-case coverage is the regions of lower observability from sensor nodes, so objects moving along this path have the minimum probability to be detected. Best-case coverage, however, is the regions of higher observability from sensors, thus probability of detecting an object moving along this path is maximum (Ghosh & Das 2008). These two parameters together give an insight of the coverage quality of the network and can help to decide if additional sensors must be deployed. Different approaches have been proposed in the literature for the worst- and best-case coverage problems (Meguerdichian et al. 2001; Huang & Tseng 2003; Veltri & Huang 2003).

A Voronoi approach based on the notion of *exposure* to evaluate the coverage of a sensor network has been proposed (Meguerdichian et al. 2001; Megerian et al. 2005). To solve the worst-case coverage problem, a very similar concept, i.e., *maximal breach path* is used. It is the path through a sensing field between two points such that the distance from any point on the path to the closest sensor is maximized. Since the line segments of the Voronoi diagram have the maximum distance from the closest sites, the maximal breach path must lie on the line segments of the Voronoi diagram corresponding to the sensor nodes (Figure 2.11). The Voronoi diagram of the sensor nodes is first constructed. This diagram is then considered as a weighted graph, where the weight of each edge is the minimum distance from the closest sensor. Finally, in order to find the maximal breach path, the algorithm performs a binary search between the smallest and largest edge weight as well as breadth-first-search to check the existence of a path from the starting to the ending points.

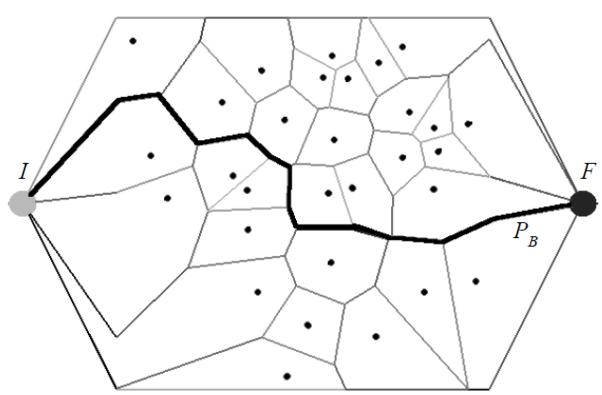


Figure 2.11: Sensor field with weighted Voronoi diagram and maximal breach path (Meguerdichian et al. 2001)

The best-case coverage problem is solved through the similar concept of *maximal support path*. This is the path through a sensing field between two points for which the distance from any point on it to the closest sensor is minimized. Intuitively, this is traveling along straight lines connecting sensor nodes. Delaunay triangulation produces triangles that have minimal edge lengths among all possible triangulations. Thus, maximal support path must lie on the lines of the Delaunay triangulation of the sensors (Figure 2.12). Delaunay triangulation of the sensor nodes is constructed and considered as a weighted graph, where the weight of each edge is the length of that edge. The maximal support path is found through an algorithm that uses breath first and binary searches of the best-case coverage of the network.

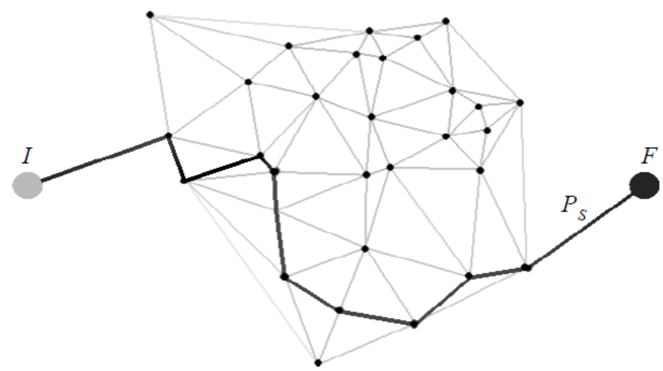


Figure 2.12: Sensor field with weighted Delaunay triangulation and maximal support path (Meguerdichian et al. 2001)

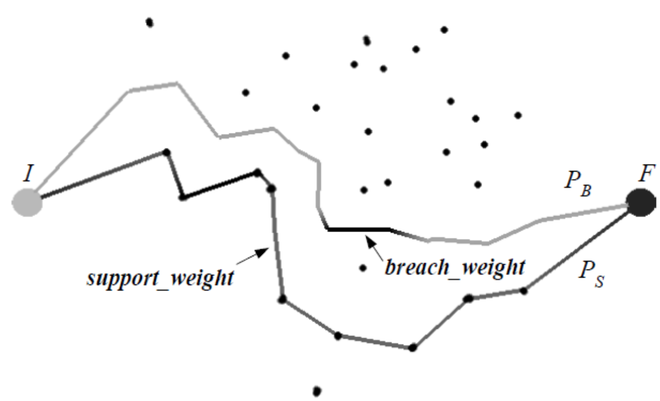


Figure 2.13: Sensor field with maximal breach path (P_B) and maximal support path (P_S) (Meguerdichian et al. 2001)

2.7 Optimization Algorithms in Geosensor Networks Deployment

Having detected the visual coverage holes by using mentioned approaches such as Voronoi diagrams; an optimization algorithm may relocate sensors in order to heal the holes. In a broad view, the existing approaches to optimally place the sensors are classified into local and global methods. Before explaining these approaches in sensor network deployment, it is necessary to introduce the concept of optimization and its general categories.

2.7.1 General Concept of Optimization and its Categories

We are facing many opportunities in our lives to optimize our tasks. Finding the shortest path to work, the optimum time to be at the bus station for minimum waiting, and choosing among the daily duties to tackle first are some examples. Optimization is the process of adjusting the inputs to or characteristics of a device, mathematical process, or experiment to find the minimum or maximum output or result (Figure 2.14). The input includes the variables; the process or function is called the cost function, objective function, or fitness function; and the output is the cost or fitness (Dr´eo et al. 2006).

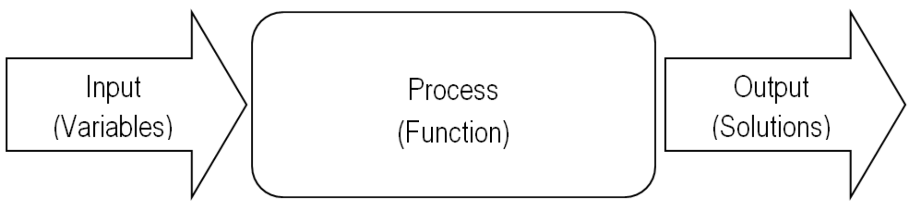


Figure 2.14: Diagram of an optimization process

Optimization algorithms can be divided into six categories, which are not necessarily mutually exclusive (Haupt et al. 2004) (Figure 2.15). For example, a single variable optimization algorithm can be either constrained or unconstrained. In the following these categories will be described shortly:

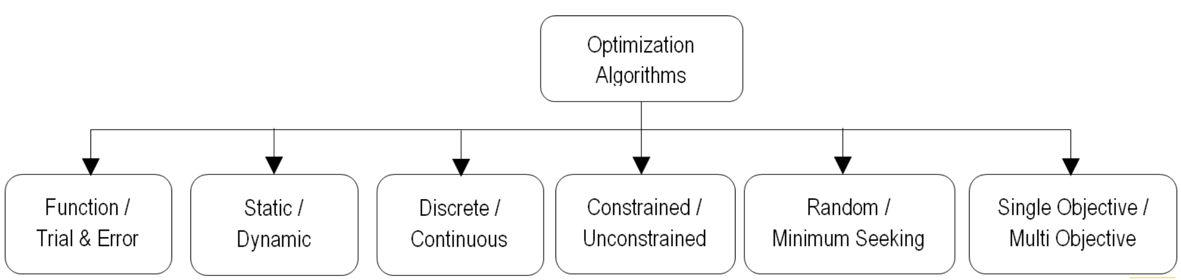


Figure 2.15: Categories of optimization algorithms

- *Trial-and-error* means that the optimization process finds the outputs without knowing much about the process of producing the results. In *function* optimization, a mathematical formula is rather used to describe the objective function.
- *Dynamic* optimization refers to the optimization process in which the output is a function of time, while in *static* optimization the output is independent of time. Adding time in dynamic optimization increases the difficulty of solving the problem due to the variations of solutions depending to the time. For example, in a dynamic optimization where we are looking for the fastest route, the shortest path is not necessarily the fastest one due to dependency of the traffic, speed limits, weather, accidents, and so on.
- Optimization algorithms may differ with their variables being *discrete* or *continuous*. Discrete variables have a finite number of possible values, whereas continuous variables have an infinite number of possible values. The application may be different, e.g., ordering a series of tasks on a list is done by using a discrete optimization, while continuous optimization is used to find the minimum value of a function over a series of real numbers.
- In most optimization problems there are always restrictions imposed by the particular characteristics of the environment or available resources (e.g., physical limitations, time restrictions, etc.). These restrictions must be satisfied in order to consider a certain solution acceptable. All these restrictions in general are called constraints, and they describe dependences among decision variables and constants (or parameters) involved in the problem. In *unconstrained* optimization any values may be taken by the variables, while in *constrained* optimization variable equalities and inequalities are incorporated into the cost function. A simple example of constrained optimization is minimizing $f(x)$ over the interval $-1 \leq x \leq 1$.
- *Convex* optimization algorithms minimize the convex functions over convex sets by starting from an initial set of variable values by using the traditional calculus methods. In mathematics a function is called convex if the line segment between any two points on the graph of the function lies above the graph, in a Euclidean space of at least two dimensions. The advantage of these algorithms is that if a local minimum exists, then it is a global minimum. The other characteristic of convex

optimization is that for each strictly convex function, if the function has a minimum, then the minimum is unique. Many optimization problems can be reformulated as convex minimization problem. For example, the problem of maximizing a concave function f can be re-formulated equivalently as a problem of minimizing the function $-f$, which is convex. *Random (non-convex)* algorithms use probabilistic calculations to find the results. Contrary to convex algorithms, they do not require the gradient of the problem to be optimized. Hence, they can be used on functions that are not continuous or differentiable. These methods are also known as direct-search, derivate free, or black-box methods.

- The optimization is *single-objective* if only one variable is supposed to be optimized. *Multi-objective* optimization deals with the task of simultaneously optimizing more than one variable with respect to a set of certain constraints. Raising the number of dimensions of optimization makes optimization process increasingly difficult. In some cases the optimization of one objective leads to the optimization of the others, which should not be considered as multi-objective optimization problem. Examples of such problems appear in several fields including network analysis, finance, oil industries, and so on (Bandyopadhyay & Saha 2013).

Having introduced the general concept of optimization and its categories, the next subsection presents the global and local optimization methods as used in the sensor network deployment.

2.7.2 Global Optimization Approaches in Sensor Network Deployment

Global optimization approaches are used to find the global maximum or minimum of a function. These approaches usually deal with the entire region of interest and look for the optimum of a function inside the whole search area. Therefore, having general knowledge over the entire search area, its characteristics and its reaction to the optimization algorithm may be necessary to get the desirable results. Especially, in iterative algorithms the whole field of study may be considered during the iterations.

Several global optimization methods have been proposed for sensor network deployment in the literature. Niewiadomska-Szynkiewicz and Marks (2009) used a classical version of simulated annealing (SA) to solve the deployment problem in sensor networks and it was implemented as a computer simulation of a stochastic process. Simulated annealing is a stochastic search algorithm based on the concept of “annealing”. The stochastic methods are optimization approaches that generate and use random variables. The annealing process includes raising the temperature of a solid to a point where its atoms can freely move, and then lowering the temperature, forcing the atoms to rearrange themselves into a lower energy state (i.e., a crystallization process). During this process, the free energy of the solid is minimized (the crystalline state is the state of minimum energy of a system). The cooling schedule is crucial: If the solid is cooled too quickly, or if the initial temperature of the system is too low, it is not able to become a crystal and instead, the solid arrives at an amorphous state with higher energy. In this case, the system reaches a local minimum (a higher energy state) instead of the global minimum, i.e., the minimal energy state. The algorithmic analog of this process begins with a random guess of the cost function variable values. Heating means randomly modifying the variables, and higher heat implies greater random fluctuations. The cost function returns the output associated with a set of variables. The idea of SA in sensor network deployment is to change the sensor positions with the random movements considering the coverage improvement. Thus, if the coverage value was improved during the movements in each step of iteration, then the new sensor positions are accepted. In order to avoid trapping in to the local optima, the temperature function helps to accept the sensor positions with worse coverage at some points. At the first movements, the temperature function has bigger values to accept further worst cases to diffuse sensors over the network. Then, it gradually gets lower values in the next iterations and sensors move to the optimized positions. Figure 2.16 illustrates how the temperature function is defined as an exponential decay function.

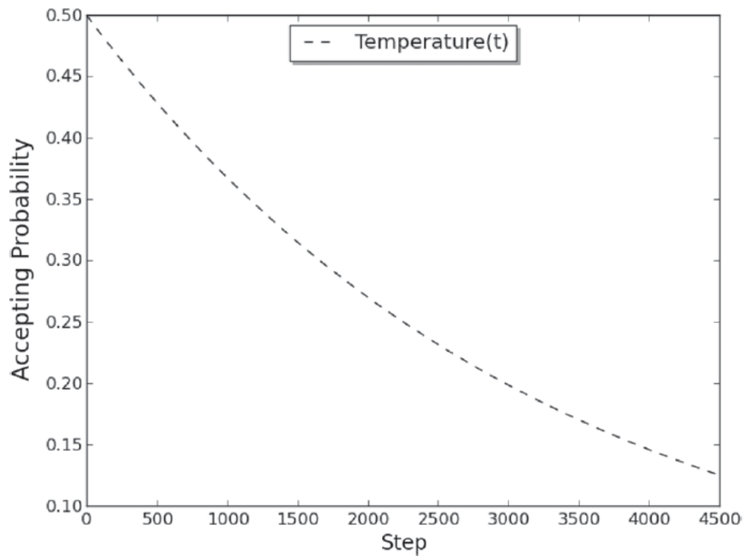


Figure 2.16: The temperature function illustration in the SA method. Here, it is assumed that the maximum number of iterations is 4550 (Akbarzadeh et al. 2013).

Akbarzadeh et al. (2013) have applied covariance matrix adaptation evolutionary strategy (CMA-ES) method in a topography aware sensor deployment. They encoded the position and orientation of the sensors inside the individuals, and then the population of individuals was evolved through generations. Finally, the individual with the best coverage is chosen as the best solution. CMA-ES is categorized as evolutionary strategy that is a stochastic optimization method for non-linear or non-convex problems. In this method, new candidate solutions are sampled according to a multivariate normal distribution. Pair-wise dependencies between the variables in this distribution are described by a covariance matrix. The covariance matrix adaptation (CMA) is a method to update the covariance matrix of this distribution.

Genetic algorithms (GA) are widely used as global optimizing intelligent techniques. The genetic algorithm is a heuristic optimization method that has been inspired by the process of natural evolution in four steps: initialization, selection, reproduction and termination. In the sensor deployment problem, the sensors are deployed using an iterative method. In each step of iteration sensor movements that provide better condition of deployment objectives are kept regarding an evolutionary procedure and other solutions (sensor movements or positions) are rejected. In case of sensor network optimization to maximize the coverage and minimize the energy consumption, the algorithm may place nodes such that both of optimal coverage and energy consumption are achieved in the entire sensor networks. Romoozi and Ebrahimpour-komleh (2010) have proposed a genetic algorithm method to create energy efficient node positioning in wireless sensor networks and showed that intelligent algorithms can extend the network lifetime by finding the optimum position of nodes. Ferentinos and Tsiligiridis (2007) applied GA for self-organizing and adaptive wireless sensor network design. They showed that optimal sensor network designs constructed by the genetic algorithm satisfy all application-specific requirements, fulfill the connectivity constraints and manage energy consumption to guarantee the maximum nodes life time. Finally, Jourdan and Weck (2004) proposed a framework that served to benchmark a multi objective genetic algorithm for sensor deployment to reach the optimum coverage and network lifetime.

2.7.3 Local Optimization Approaches in Sensor Network Deployment

Local optimization is a metaheuristic method for solving optimization problems that need hard computations. Metaheuristic methods take few assumptions about the optimization problem and often find good solutions with less computational efforts. Local search can be used on problems that can be formulated as finding a solution maximizing a criterion among a number of candidate solutions. These methods move from solution to solution in the searching space until the optimal solution is reached or a time bound is elapsed. A local optimization algorithm starts from a candidate or initial value or solution, and then iteratively moves to neighbor values or solutions. Typically, every candidate solution has more than one neighbor solution, thus choosing the next solution or value depends on the neighborhood information of the current solution as well as the previous minimum or maximum value regarding the optimization objective (this is why they are called “local search” or “local optimization”). Normally, local optimization methods are applied for solving computationally hard optimization problems that can be formulated as finding a solution maximizing a criterion among a number of candidates. Local search can achieve optimal solution in the face of purely convex optimization problems (Boyd & Vandenberghe 2009).

Cortes and Martinez (2004) proposed the gradient descent algorithm for coverage control and optimal sensing policies in mobile sensor networks. Gradient descent is an optimization algorithm which takes steps proportional to the negative of the gradient of the function at the current point to find a local minimum.

Many of the local optimization approaches use the concept of mobility, which exploits moving properties of nodes to get better coverage conditions and tries to relocate sensor nodes to optimal locations that serve maximum coverage. For sensor deployment approaches, where there is no information available about the terrain surface and its morphology, random sensor deployment is used. This method does not guarantee the optimized coverage of the sensing region. Thus, some deployment strategies take advantage of mobility options and try to relocate sensors from their initial places to optimize the network coverage. Potential field-based, virtual force-based and incremental self-deployment methods are examples of such approaches.

The idea of potential field is that every node is exposed to two forces: (i) a repulsive force that causes the nodes to repel each other, and (ii) the attractive force that makes nodes move toward each other when they are on the verge of being disconnected (Howard et al. 2002b). These forces have inverse proportion with the square of distance between nodes. Each node repels all its neighbors. This action decreased the repulsive force, but at the same time, it stimulates the attractive force. Eventually, it ends up in an arrangement where all the nodes reach an equilibrium situation and uniformly cover the sensing field.

Virtual force-based method is very similar to the potential-based methods, but here each node is exposed to three types of forces: (i) a repulsive force exerted by obstacles, (ii) an attractive force exerted by areas where the high degree of coverage is required, and (iii) attractive or repulsive force by another point based on its location and orientation (Y Zou & Chakrabarty 2004; Y. Zou & Chakrabarty 2004).

In incremental self-deployment algorithms, each node finds its optimal location through previous deployed nodes information in four steps: (i) initialization that classifies the nodes to three groups: waiting, active and deployed; (ii) goal selection that selects the best destination for the node to be deployed based on previous node deployment; (iii) goal resolution that assigns this new location to a waiting node, and specifies the plan for moving to this location; (iv) Finally, execution that deploys the active nodes in their place (Howard et al. 2002b; Howard et al. 2002a; Heo & Varshney 2003).

As illustrated in the above algorithms, spatial coverage of sensor networks is much related to the spatial distribution of the sensors in the environment. In other words, described algorithms try to distribute sensors to cover the field of interest as much as possible. Voronoi diagram and Delaunay triangulation have been used in many mobility based methods, as they directly satisfy the required distribution. We classify the Voronoi-based solutions based on the sensor types used in the network: (1) static sensor networks, (2) mobile sensor networks, and (3) hybrid sensor networks, where a combination of static and mobile sensors is deployed. For static sensor networks, new sensors are added. For mobile and hybrid networks, however, existing sensors move to heal the holes. To the best of our knowledge, there are two suggestions to deploy an additional sensor to heal the holes in a static sensor network. Ghosh (2004) proposes that for each Voronoi vertex, one node should be added to heal the coverage hole around this Voronoi vertex. In mobile sensor networks, all sensors have the ability to move in order to heal the holes. Wang et al. (2006) proposes three Voronoi-based strategies for this movement: Vector-based (VEC), Voronoi-based (VOR), and Minimax. They all are iterative approaches and gradually improve the coverage of the sensor network. These approaches and their integration to the sensor network deployment will be fully described in Chapter 3. New local optimization methods and framework are also given out in Chapter 3 and 4, which consider the environmental elements and contextual information.

2.8 Conclusion

An overview of sensor networks and its technology were presented at the beginning of this chapter. Then, wireless sensor network problems as well as a wide range of technical challenges have been introduced. The coverage problem was been presented as one of the most important challenges in geosensor networks. Many fundamental sensor network issues such as location, deployment, topology, connectivity, and spatial modeling have been investigated in this chapter due to their direct impact on the network coverage. In order to address the coverage problem, brief information of spatial modeling issues in sensor network deployment is necessary. Then, a survey over the sensing, and communication models in sensor networks was carried out. Then, the concept of optimization was introduced and its categories were discussed to illustrate how optimization algorithms may integrate in sensor network deployment. Especially, algorithms that use Voronoi diagram and Delaunay triangulation were intensively investigated. As discussed in the chapter, most of the existing methods oversimplify the coverage problem and do not consider the characteristics of the environment where they are deployed. Spatial coverage of sensor networks is related to the spatial distribution of the sensors in the environment. The coverage determination algorithms try to distribute the sensors in the field so that the maximum coverage is obtained.

Voronoi diagram and Delaunay triangulation are well adapted for abstraction and modeling of sensor networks and spatial data structures. However, their application is still limited when it comes to the determination and optimization of spatial coverage of more complex sensor networks (e.g., sensor networks in the presence of obstacles). To overcome the limitation of these methods, novel approaches based on the Voronoi diagram are proposed in the next chapters, which consider spatial information in sensor network deployment and coverage optimization.

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CHAPTER 3

A GIS based Wireless sensor network Coverage Estimation and Optimization: A Voronoi approach

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3.1 Abstract

Recent advances in sensors technology have resulted in the design and development of a variety of geosensor networks and their applications in many disciplines. Such networks consist of a set of sensors in different locations and sensing various real world phenomena for environmental monitoring, object surveillance, tracking and controlling applications. A fundamental issue in a geosensor network optimization is estimation of its spatial coverage. The existence of various obstacles in the sensing environment and its complexity result in several uncovered areas or holes in the sensing environment. These holes should be detected and minimized using an optimization process. Different approaches have been proposed in the literature to resolve this problem. Many of these approaches use Voronoi diagram and Delaunay triangulation to identify visual holes in the network and create an optimal arrangement of sensors to reduce uncovered areas. However, most of these methods over simplify the environment in which the sensor network is deployed reducing the quality of spatial coverage estimation and optimization. This paper presents a survey of the existing solutions for geosensor network optimization that use Voronoi diagram and

Delaunay triangulation and identifies their limitations in a real world application. Next, it proposes a more realistic approach by integrating spatial information in the optimization process based on Voronoi diagram. Finally the results of two cases studies based on the proposed approach in a natural area and urban environment are presented and discussed.

3.2 Introduction

Recent advances in electrical, mechanical and communication systems have resulted in the development of efficient low cost and multi-function sensors. These tiny and ingenious devices are usually deployed in a wireless network to monitor and collect physical and environmental information such as motion, temperature, humidity, pollutants, traffic flow, etc. The information is then communicated to a process center where it is integrated and analyzed for different applications. Deploying sensor networks allows inaccessible areas to be covered by minimizing the sensing costs compared to the use of separate sensors to completely cover the same area. Sensors may be spread with various densities from 10 meter apart to as high as 20 nodes per square meter depending on the application and the details and the quality of the information required.

Despite the advances in the sensor network technology, the efficiency of a sensor network for collection and communication of the information may be constrained by the limitations of sensors deployed in the network nodes. These restrictions may include sensing range, battery power, connection ability, memory, and limited computation capabilities. Many researchers have addressed these limitations in recent years from various disciplines in order to design and deploy more efficient sensor networks (Nittel 2009).

Efficient sensor network deployment is one of the most important issues in sensor network domain that affects the coverage and communication between sensors in the network. Nodes use their sensing modules to detect events occurring in the region of interest. Each sensor is assumed to be a visual camera that has a sensing range, which may be constrained by the phenomenon being sensed and the environment conditions. Hence, obstacles and environmental conditions affect network coverage and may result in visual holes in the sensing area. Communication between nodes is also important. Information collected from the region should be transferred to a processing center, directly or via adjacent nodes. In the latter case, each node needs to be aware of the position of other adjacent sensor nodes in their proximity.

Several approaches have been proposed to detect and eliminate holes and hence increase sensor network coverage through optimization methods. Many of these approaches use the Voronoi diagram and Delaunay triangulation to identify sensing holes in the network and create an optimal arrangement of the sensors to eliminate the holes. However, most of these methods over simplify the environment in which the sensor networks are deployed reducing the quality of spatial coverage estimation and optimization. This paper makes a critical overview of the existing solutions based on Voronoi diagrams and Delaunay triangulation for geosensor network coverage estimation and optimization. Next, it proposes a novel sensor network deployment approach by integrating spatial information in the optimization process based on Voronoi diagram.

The remainder of this paper is as follows. Section 3.3 presents a state of the art on the geosensor networks and their related issues. Section 3.4, describes the coverage problem in geosensor networks and different solutions found in the literature for its estimation and optimization. Section 3.5 presents the coverage determination and optimization solutions based on Voronoi and Delaunay triangulation and their limitations. Section 3.6 proposes a novel sensor network deployment approach by integrating spatial information in the optimization process based on Voronoi diagram. In section 3.7, we present the results of the two experimentations based on the proposed approach both in natural and urban areas. Finally, section 3.8 concludes the paper and proposes new avenues for future work.

3.3 State of the art on Geosensor Networks and their applications

Sensor networks were announced as one of the most important technologies for the 21st century in 1999 by Business Week (Anon 1999). These networks are usually composed of a set of small, smart and low-cost sensors with limited on-board processing capabilities, storage and short-range wireless communication links based on radio technology. Previously, sensor networks consisted of small number of sensor nodes that were usually wired to a central processing station. However, nowadays, the focus is more on wireless, distributed, sensing nodes (Bharathidasan & Ponduru 2004; Szewczyk et al. 2004; Worboys & Duckham 2006). A sensor node is characterized by its sensing field, memory and battery power as well as its computation and communication capabilities. A sensor can only cover a small area. However, collaboration of a group of sensors with each other can cover a more significant sensing field and hence accomplish larger tasks. Each element of a group of sensors can sense and collect data from the environment, apply local processing, communicate it to other sensors and perform aggregations on the observed information (Sharifzadeh & Shahabi 2004).

Sensor networks are also referred to as Geosensor networks as they are intensively used to acquire spatial information (Nittel 2009). Hereafter, we will use both of the terms "sensors" and "geosensors" interchangeably. Geosensors can be deployed on the ground, in the air, under water, on bodies, in vehicles, and inside buildings.

Sensor networks have several applications including environmental monitoring, change detection, traffic monitoring, border security, and public security, etc. They are used for collecting the information needed by smart environments quickly and easily, whether in buildings, utilities, industries, home, shipboard, transportation systems automation, or elsewhere. Sensor networks are useful in vehicle traffic monitoring and control. Most traffic intersections have either overhead or buried sensors to detect vehicles and control traffic lights. Furthermore, video cameras are frequently used to monitor road segments with heavy traffic, with the video sent to human operators at central locations (Chong & Kumar 2003). Sensor networks can be used for infrastructure security in critical buildings and facilities, such as power plants and communication centers. Networks of video, acoustic, and other sensors provide early detection of possible threats (Soro & Heinzelman 2005). Commercial industries have long been interested in sensing as a means of lowering cost and improving machine (and perhaps user) performance and maintainability. Monitoring machine "health" through determination of vibration or wear and lubrication levels, and the insertion of sensors into regions inaccessible by humans, are just two examples of industrial applications of sensors (Chong & Kumar 2003). A broad classification of geosensor network applications is monitoring continuous phenomena (e.g., to assess plant health and growth circumstances, or to observe and measure geophysical processes), detecting real time events (e.g., flood and volcano), and tracking objects (e.g., animal monitoring) (Nittel 2009; Szewczyk et al. 2004; Worboys & Duckham 2006).

Sensor networks have some limitations when it comes to the modeling, monitoring and detecting environmental processes. Monitoring and analyzing dynamic objects in real time are also difficult. Examples of such processes include the observations of dynamic phenomena, (e.g., air pollution) or monitoring of mobile objects (e.g., animals in a habitat). It is necessary to know how to use this technology to detect and monitor those phenomena appropriately and efficiently. For this purpose, one needs to identify the relevant mix of hardware platforms for the phenomena type, the accessibility or inaccessibility of the observation area, hazardous environmental conditions, and power availability, etc. Today wireless sensor network technology are more effectively used for detecting and monitoring time-limited events (e.g., earthquake tremors), instead of continuous sampling in remote areas due to the battery constraints of geosensor platforms (Nittel 2009).

3.4 Coverage Problem in Geosensor Networks

An important issue to deploy a sensor network is finding the best sensor location to cover the region of interest. Definition of coverage differs from one application to another. The so-called art gallery problem, for example, aims to determine the minimum number of required observers (cameras) to cover an art gallery room such that every point is seen by at least one observer (De Berg et al. 2000). Here, coverage means the visual coverage and defined based on a direct visibility between the observer and the target point. In sensor networks, however, the coverage of a point means that the point is located in the sensing range of a sensor node, which is usually assumed to be uniform in all directions. In this case, the sensing range is represented by a disk around the sensor (Ahmed et al. 2005). Failing this condition for some points in the region of interest will result in coverage holes (Figure 3.1).

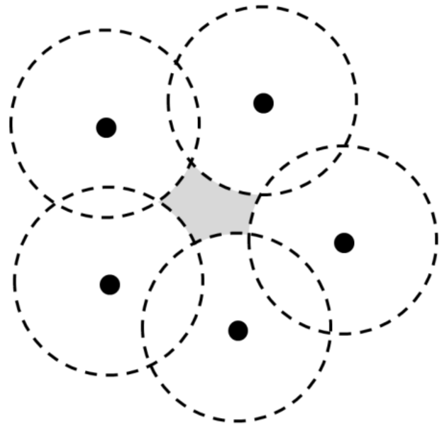


Figure 3.1: Coverage hole (shaded region) in a sensor network with disk model sensing range

Regarding this definition of coverage in sensor networks, the coverage problem basically means placing a minimum number of nodes in an environment, such that every point in the sensing field is optimally covered regarding the initial considerations (Aziz et al. 2009; Ghosh & Das 2008). Nodes can either be placed manually at predetermined locations or dropped randomly in the environment. It is difficult to find a random scattering solution that satisfies all the coverage and connectivity conditions. Thus, the term of area coverage plays an important role in sensor networks and their connectivity.

Existing solutions to determine and optimize the coverage in sensor networks can be classified in two main categories of "exposure based" and "mobility based" approaches (Ghosh & Das 2008). Exposure based solutions evaluate unauthorized intrusions in the networks. Mobility based solutions, however, exploit moving properties of nodes to get better coverage conditions and try to relocate sensor nodes to optimal locations that serve maximum coverage.

3.4.1 Coverage Based on Exposure

The estimation of visual coverage can be defined as a measure of the ability to detect objects within a sensor direct sensing range. The notion of exposure represents such a measurement. It is described as the expected average ability to observe a target moving in a sensor field. It is related to coverage in the sense that "it is an integral measure of how well the sensor network can observe an object [exists in the field or] moving on an arbitrary path, over a period of time" (Megerian et al. 2002).

A very simple, but nontrivial example of exposure problem is illustrated in Figure 3.2. An object moves from point *A* to point *B* and there is only one sensor node *S* in the field. Obviously, the path 2 has the maximum exposure, because it is the shortest path from *A* to *B* and it passes through the sensor node *S*. Thus, an object moving along this path is certainly tracked by *S*. However, finding the path with the minimum exposure is tricky: although path 1 is the farthest path from the sensor node *S* and so intuitively seems to have the lowest exposure, it is also the longest path. Therefore, travelling along this path takes a longer time and the sensor has a longer time to track the moving object. It is shown that the minimum exposure path is 3, which is a trade-off between distance from the sensor and travelling time (Huang & Tseng 2005).

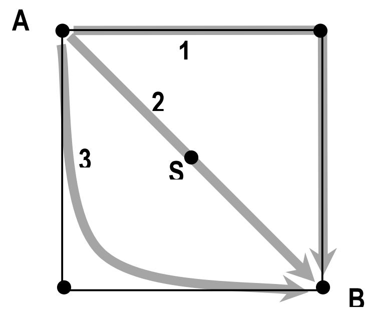


Figure 3.2: Minimum and maximum exposure paths in a simple sensor network (Huang & Tseng 2005)

The so-called worst case and best case coverage are examples of methods for exposure evaluation (Megerian et al. 2005; Meguerdichian, Koushanfar, et al. 2001). Worst-case coverage includes regions of lower observability from sensor nodes, so objects moving along this path have the minimum probability to be detected. Best-case coverage, however, includes regions of higher observability from sensors, thus probability of detecting an object moving along this path is maximum (Ghosh & Das 2008). These two parameters together give an insight of the coverage quality of the network and can help to decide if additional sensors must be deployed. Different approaches have been proposed in the literature for the worst- and best-case coverage problems (Huang 2003; Megerian et al. 2002; Meguerdichian, Slijepcevic, et al. 2001; Gau & Peng 2006; Veltri & Huang 2003). A Voronoi based solution for this problem is presented in Section 3.5.

3.4.2 Coverage Based on Mobility

In some sensor placement approaches, where there is no information available about the terrain surface and its morphology, random sensor placement is used. This method does not guarantee the optimized coverage of the sensing region. Thus, some deployment strategies take advantage of mobility options and try to relocate sensors from their initial places to optimize the network coverage. Potential field-based, virtual force-based and incremental self-deployment methods (Howard et al. 2002a; Howard et al. 2002b; Zou & Chakrabarty 2004) are examples of such approaches summarized here. Other methods such as VEC, VOR and MiniMax, which are mobility-based methods that use the Voronoi diagram in their approach, are explained in the next section.

The idea of the potential field method is that every node is exposed to two forces: (i) a repulsive force that causes the nodes to repel each other, and (ii) an attractive force that makes nodes move toward each other when they are on the verge of being disconnected (Ghosh & Das 2008; Howard et al. 2002b). These forces have inverse proportion with the square of distance between nodes. Each node repels all its neighbors. This action decreases the repulsive force, but at the same time, it stimulates the attractive force. Eventually, it ends up in an arrangement in which all the nodes reach an equilibrium situation and uniformly cover the sensing field.

The virtual force-based method is very similar to potential-based, but here each node is exposed to three types of forces: (i) a repulsive force exerted by obstacles, (ii) an attractive force exerted by areas where a high degree of coverage is required, and (iii) attractive or repulsive forces by another point based on its location and orientation (Zou & Chakrabarty 2004).

In the incremental self-deployment algorithm, each node finds its optimal location through previous deployed nodes information in four steps (Heo & Varshney 2003; Howard & Mataric 2002; Howard et al. 2002a): (i) initialization that classifies the nodes into three groups: waiting, active and deployed; (ii) goal selection that selects the best destination for the node to be deployed based on previous node deployment; (iii) goal resolution that assigns this new location to a waiting node and the plan for moving to this location is specified; (iv) Finally, execution deploys the active nodes to their places.

As it is described in the above algorithms, spatial coverage of sensor networks is much related to the spatial distribution of the sensors in the environment. In other words, these algorithms attempt to distribute sensors to maximize the coverage of an environment of interest. Voronoi diagram and Delaunay triangulation are data structures that directly satisfy the required distribution. They have been used for developing algorithms for both exposure and mobility based approaches.

3.5 Role of Voronoi diagram and Delaunay triangulation

This section presents the solutions for sensor network coverage optimization that use Voronoi diagram and Delaunay triangulation for coverage determination and optimization in sensor networks. The solutions are categorized as coverage hole detection, healing the holes, and node scheduling. Some other challenges are introduced at the end of this section.

3.5.1 Coverage Hole Detection

In a simple sensor network – where the visual sensing regions of all sensors are identical circles – if a point is not covered by its closest sensor node, obviously it is not covered by any other sensor node. This characteristic is the basis of using Voronoi diagrams in sensor coverage problem. In a Voronoi diagram, all the points within a Voronoi cell are closest to the generating node that lies within this cell. Thus, having constructed the Voronoi diagram of the sensor nodes and overlaid the sensing regions on it (Figure 3.3), if a point of a Voronoi cell is not covered by its generating node, this point is not covered by any other sensor (Ahmed et al. 2005; Ghosh 2004; Wang et al. 2009; Wang et al. 2003). Although computing the area of a Voronoi cell is straightforward, computing the area of the uncovered region in a Voronoi cell is a complicated task, because the sensing regions may protrude the Voronoi cells and overlay each other. Strategies for this computation can be found in (Ghosh 2004; Wang et al. 2003).

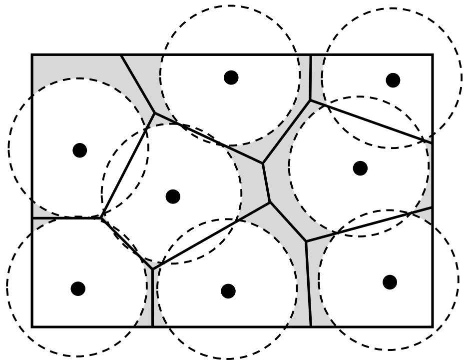


Figure 3.3: Using Voronoi diagram to detect the coverage holes (shaded regions) in a sensor network

Another Voronoi-based approach to evaluate the coverage of a sensor network is based on the notion of exposure, which was discussed earlier in section III. To solve the worst-case coverage problem, a very similar concept, i.e., maximal breach path is used. It is the path through a sensing field between two points such that the distance from any point on the path to the closest sensor is maximized. Since the line segments of the Voronoi diagram have the maximum distance from the closest sites, the maximal breach path must lie on the line segments of the Voronoi diagram corresponding to the sensor nodes (Figure 3.4). The Voronoi diagram of the sensor nodes is first constructed. This diagram is then considered as a weighted graph, where the weight of each edge is the minimum distance from the closest sensor. Finally, an algorithm uses breadth first and binary searches to find the maximal breach path (Megerian et al. 2005; Meguerdichian, Koushanfar, et al. 2001).

The best-case coverage problem is solved through the similar concept of maximal support path. This is the path through a sensing field between two points for which the distance from any point on it to the closest sensor is minimized. Intuitively, this is traveling along straight lines connecting sensor nodes. Since the Delaunay triangulation produces triangles that have minimal edge lengths among all possible triangulations, maximal support path must lie on the edges of the Delaunay triangulation of the sensors (Figure 3.5). Delaunay triangulation of the sensor nodes is constructed and considered as a weighted graph, where the weight of each edge is the length of that edge. The maximal support path is found through an algorithm that uses breadth first and binary searches (Megerian et al. 2005; Meguerdichian, Koushanfar, et al. 2001).

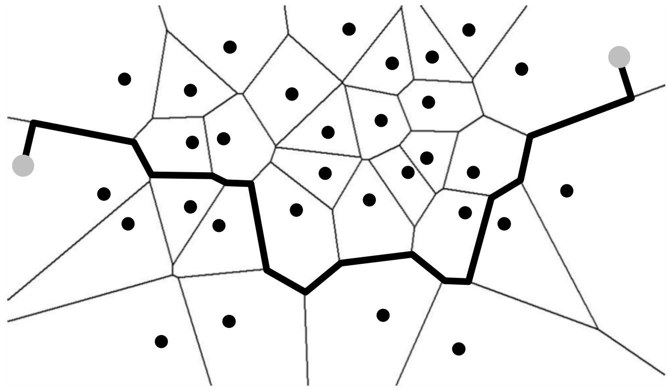


Figure 3.4: Maximum breach path in a sensor network and its connection to Voronoi diagram

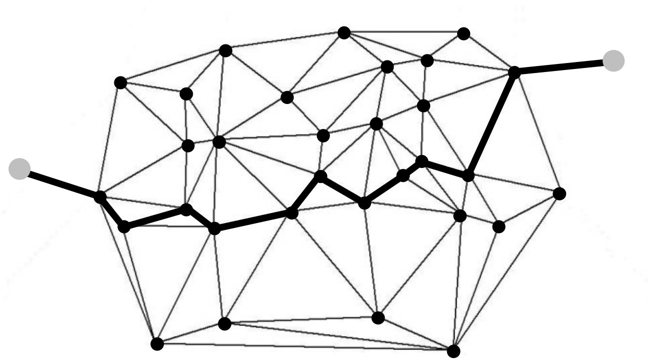


Figure 3.5: Maximum support path in a sensor network and its connection to Delaunay triangulation

3.5.2 Healing the Holes

Having detected the visual coverage holes by overlaying the sensors sensing range and sensor node corresponding Voronoi cell, the sensors must be relocated in order to heal the holes. For this, we classify the Voronoi-based solutions based on the sensor types used in the network: (1) Static sensor networks, (2) mobile sensor networks, and (3) hybrid sensor networks, where a combination of static and mobile sensors is deployed. For static sensor networks, new sensors are added. For mobile and hybrid networks, existing sensor nodes move to heal the holes.

3.5.2.1 Static Sensor Networks

To the best of our knowledge, there are two suggestions to deploy an additional sensor to heal the holes in a static sensor network. Ghosh (2004) proposes that for each Voronoi vertex, one node should be added to heal the coverage hole around this Voronoi vertex. As Figure 3.6 shows, to heal the hole around Voronoi vertex v_2, the target location p_1 lies on the bisector of the angle $v_1v_2v_3$ and $d(s, p_1) = \min\{2R, d(s, v_2)\}$, where d is the

Euclidean distance and R is the sensing radius of the sensors. Wang, Cao, and LaPorta (2003), however, deploy only one mobile node to heal the coverage hole of a Voronoi cell. As illustrated in Figure 3.6, the target location p_2 lies on the line connecting the sensor node and its furthest Voronoi vertex (v_4 here) and $d(s, p_2) = \max\{\sqrt{3}R, d(s, v_4)\}$.

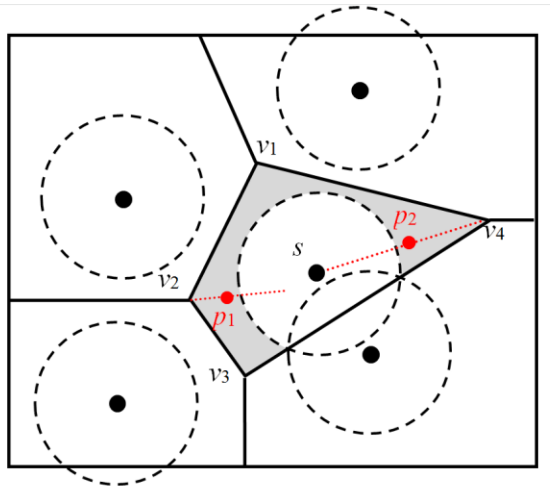


Figure 3.6: Deploying an additional sensor to heal the hole in a static sensor network

3.5.2.2 Mobile Sensor Networks

In mobile sensor networks, all sensors have the ability to move in order to heal the holes. Wang, Cao, and Porta (2006) propose three Voronoi-based strategies for this movement: Vector-based (VEC), Voronoi-based (VOR), and Minimax. They all are iterative approaches and gradually improve the coverage of the sensor network.

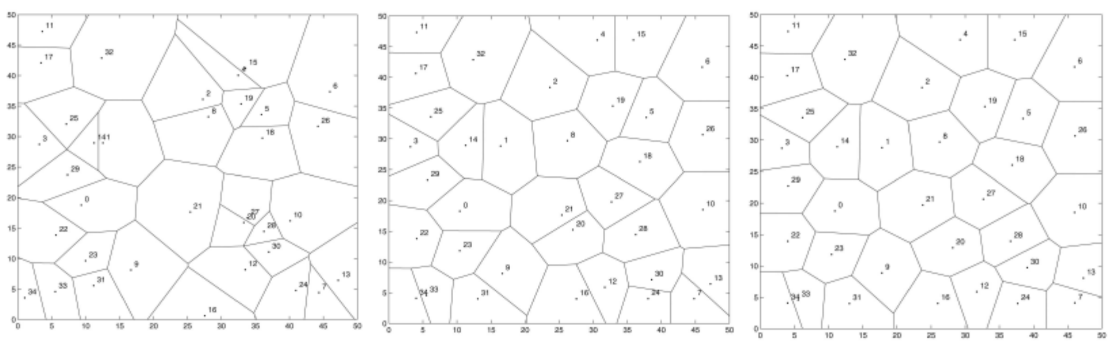
VECtor-based Algorithm (VEC)

VEC pushes sensors away from a densely covered area. It imitates the electromagnetic force that exists between two particles: if two sensors are too close to each other, they exert a repulsive force. By knowing the target area and the number of sensors, an average distance between the sensors, d_{avg} can be calculated beforehand. If the distance between two sensors s_i and s_j is smaller than d_{avg} and neither of their Voronoi cells is completely covered, the virtual force pushes them to move $(d_{avg} - d(s_i, s_j))/2$ away from each other.

However, if one of the sensors completely covers its Voronoi cell, and so it should not move, then the other sensor pushes $(d_{avg} - d(s_i, s_j))$ away.

In addition to the repulsive forces between sensors, the boundaries also exert forces to push sensors that are too close to the boundary inside. If the distance of the sensor i, i.e., $d_b(s_i)$, from its closest boundary is smaller than $d_{avg}/2$, then it moves $(\frac{d_{avg}}{2} - d_b(s_i))$ toward the inside of the network.

Note that movements of the sensors change the shape of the Voronoi cells, which may result in decreasing the coverage in the new configuration. Thus, the sensors move to the target position only if their movements increase the local coverage within their Voronoi cell. Otherwise, a node takes the midpoint position between its current and target positions, as the new target position, and again check the improvement, and so on. This process is called movement adjustment). Figure 3.7 shows an example of using VEC algorithm.



Round 0 Round 1 Round 2

Figure 3.7: An example of using VEC algorithm to move the sensors (Wang et al. 2006)

VORonoi-based Algorithm (VOR)

Unlike VEC algorithm, VOR is a pulling strategy so that sensors cover their local maximum coverage holes. In this algorithm, each sensor moves toward its furthest Voronoi vertex until this vertex is covered (Figure 3.8). The movement adjustment mentioned for VEC is also applied here. Furthermore, VOR is a greedy algorithm that heals the largest hole. However, after moving a sensor, a new hole may be created that is healed by a reverse movement in the next iteration, so it results in an oscillation movement. An oscillation control is added to overcome this problem. This control does not allow sensors to move backward immediately: Before a sensor moves, it first checks if the direction of this moving is opposite to that in the previous round. If so, it stops for one round to see if the hole is healed by the movement of a neighboring sensor. Figure 3.9 shows an example that moves the sensors based on VOR algorithm.

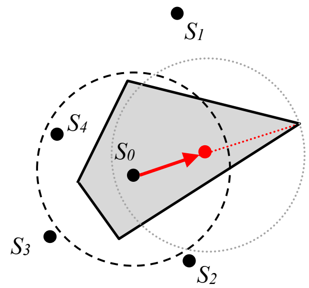


Figure 3.8: Movement of a sensor in VOR algorithm

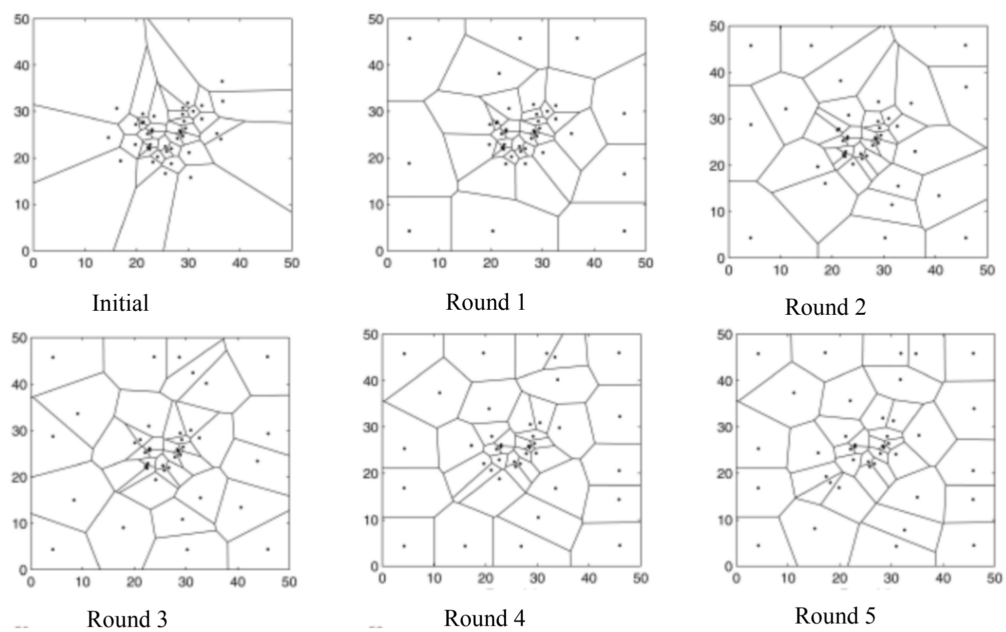


Figure 3.9: An example of using VOR algorithm to move the sensors (Wang et al. 2006)

Minimax Algorithm

This algorithm is based on the fact that when the sensors are evenly distributed, a sensor should not be too far away from any of its Voronoi vertices. In other words, the disadvantage of VOR algorithm is that it may result in a case where a vertex that was originally close becomes a new farthest vertex. The MiniMax algorithm solves this by choosing the target location as the point inside the Voronoi cell whose distance to the farthest Voronoi vertex is minimized. This point, which is called Minimax point, is the center of the smallest enclosing circle of the Voronoi vertices and can be calculated by the algorithms described in (Megiddo 1983; Skyum 1991; Welzl 1991). Minimax algorithm has some advantages. Firstly, it can reduce the variance of the distances to the Voronoi Vertices, resulting in more regular shaped Voronoi cells, which better utilizes the sensor's sensing circle. Secondly, Minimax considers more information than VOR, and it is more conservative. Thirdly, Minimax is more "reactive" than VEC, i.e., it heals the hole more directly by moving toward the farthest Voronoi vertex.

3.5.2.3 Hybrid Sensor Networks

In a hybrid sensor network, having detected a hole around a static sensor, a mobile sensor moves in order to heal this hole. The location to which the mobile sensor should move is computed similar to the solutions proposed for the static networks in section 3.5.2. Then, the static sensor requests the neighboring mobile sensors to move to the calculated destination. Each of the mobile sensors that have received this request calculates the coverage holes formed at its original location due to its movement. It decides to move if the new hole is smaller than the hole size of the requesting static sensor. It is noted that since movements of the mobile sensors may create new (but smaller) holes, this solution is an iterative procedure. More discussion on this movement and its technical considerations (e.g., bidding protocols) can be found at Ghosh (2004) and Wang et al. (2003) .

3.5.3 Node Scheduling

As mentioned earlier, energy is an important issue in sensor networks. Thus, strategies to save energy are interested in these regards. A relevant case to save the energy is turning temporarily some sensor nodes to sleep mode in the multi-covered areas. This is also important to avoid other problems (e.g., the intersection of sensing area, redundant data, and communication interference), in areas with a high density of sensor nodes (Vieira et al. 2003). Different methods have been proposed for this problem (Ruiz et al. 2003; Tian & Georganas 2002).

Vieira et al. (2003) proposed a Voronoi-based algorithm to find the nodes to be turned on or off. The Voronoi diagram of the sensor nodes is constructed. Each Voronoi cell represents the area that the corresponding node is responsible for. The sensors whose responsible areas are smaller than a predefined threshold are turned off. By updating the Voronoi diagram, the neighbors of that sensor become responsible for that area. This process continues until there is no node responsible for an area smaller than the given threshold.

3.5.4 Other Challenges

This section introduces more complicated issues in sensor coverage problem that can be dealt with using Voronoi diagram and Delaunay triangulation.

3.5.4.1 K-coverage Sensor Networks

In some applications, such as military or security control, it is required that each point of the region is covered by at least k ($k>1$) sensors. Among different solutions proposed in the literature (Zhou et al. 2004), So and Ye (2005) have developed an algorithm based on the concept of Voronoi regions. Suppose that $P = \{p_1, p_2, \ldots, p_n\}$ is a set of n point in $\boldsymbol{R}^n$. For any subset U of P, the Voronoi region of U is set of points in $\boldsymbol{R}^n$ closer to all points in U than to any point in P-U. The proposed algorithm can check the k-coverage for the area, but developing the algorithms to heal the holes is still an open question.

3.5.4.2 Sensor Networks with Various Sensing Ranges

So far, we have assumed that all sensors are identical. In reality, however, a sensor network could be composed of multiple types of sensors with different specifications, including their sensing range and sensing model (e.g., circular, ellipsoidal or irregular sensing model (Ahmed et al. 2005; So & Ye 2005)). A weighted Voronoi diagram is a solution in such cases to examine the coverage quality of the network (Figure 3.10) (So & Ye 2005). However, to the best of our knowledge, the movement strategies have not been researched deeply for such heterogeneous sensor networks.

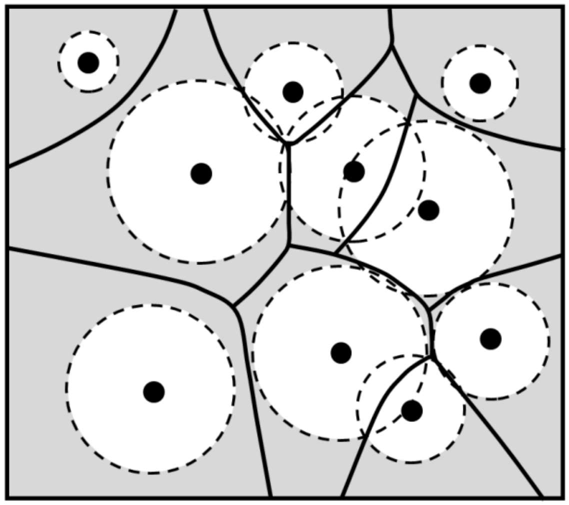


Figure 3.10: Using weighted Voronoi diagram to examine the coverage quality of a sensor network with various sensing ranges

3.5.4.3 Directional Sensor Networks

Coverage determination for directional sensor networks (i.e., networks composed of sensor with limited field of views) is a practical area of research. Adriaens et al. (2006) have extended the previous researches (Megerian et al. 2005; Meguerdichian, Koushanfar, et al. 2001) and developed a Voronoi-based algorithm to detect the worst-case coverage (maximal breach path) in such networks.

3.5.4.4 Sensor Networks in a 3D Environment

The approaches mentioned in this paper assume that a sensor network is deployed in a 2D flat environment (i.e., a 2D Euclidean plane). However, this assumption oversimplifies sensor network reality. The real world is mostly 3D heterogeneous environment, which may contain obstacles (Figure 3.11). Hence, 3D sensor networks have considerable interest in diverse applications including structural monitoring networks and underwater networks (Huang et al. 2004). In addition to the form and the relief of the sensor network area, various obstacles may prevent the sensors from covering an invisible region or communicating data between each other.

Several algorithms have been proposed for the coverage problem of 3D sensor networks (Bahramgiri et al. 2006; Chong & Kumar 2003; Huang et al. 2004). The algorithms presented here can be extended to use 3D Delaunay triangulation and Voronoi diagram for coverage determination and optimization of such sensor networks (Ghosh et al. 2007; Lei et al. 2007; Marengoni et al. 1996). There are also suggestions to use Delaunay triangulation and Voronoi diagram when the environment contains obstacles (Wu et al. 2007). Although these extensions are interesting in some applications, they may have deficiencies for the geographical fields, because they consider 3D Euclidean environment and man-made obstacles, e.g., walls. Real world environments, however, are 3D heterogeneous environments full of man-made and natural obstacles, where, even terrain could play the role of an obstacle. Using capabilities of geographical information systems (GIS) seems a promising solution in this regard, which has not been investigated. It can provide the information (e.g., digital terrain models) or spatial analyses (e.g., visibility analysis) required to evaluate and optimize the sensor networks installed in the nature environment. Hence, 3D Delaunay triangulation and Voronoi diagrams present interesting solutions for the sensor network modeling and optimization in 3D environments. However, their application is not straightforward and several challenging conceptual and implementation problems should be addressed.

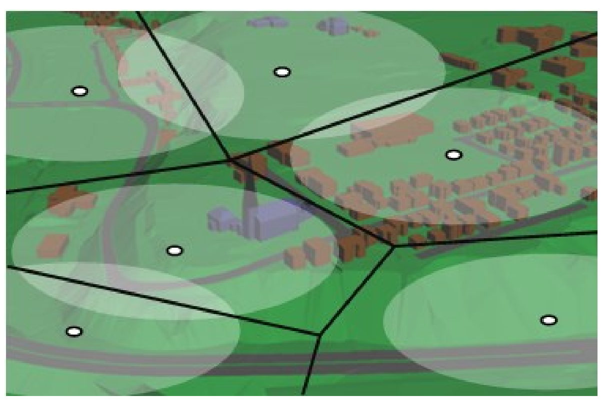


Figure 3.11: A sensor network in a 3D environment with various obstacles. The superimposed 2D Voronoi diagram cannot determine the network coverage

3.6 Proposed Approach for a Realistic Sensor Network Deployment

Although efficient sensor deployment for maximum network coverage has been extensively addressed in the literature (Sections 3.4 and 3.5), they are not adequately adopted to consider the reality of the terrain and the environment where the sensor networks are deployed. The main reasons are:

- Most of the existing solutions suffer from the lack of integrating environmental information with sensor network deployment algorithms. They do not consider the form and the topography of the area covered by the sensor network as well as various existing obstacles that may prevent the sensors from covering the whole area or allowing data communication between sensors. To carry out a realistic sensor placement scheme, it is necessary to involve the environmental information that affects sensor performance and network coverage.
- The sensor network region of interest may change over the sensing experiments. For instance, in a battlefield all parameters of the study area may rapidly change. In urban areas, new constructions may happen, urban facilities may be added or removed or changes may occur in land cover and land use information. These changes may significantly affect the sensor network coverage. Furthermore, characteristics of sensor platforms may change during the sensing steps. For example, fluctuation of the battery power for each platform decreases the sensing range of nodes, so the network arrangement must be modified to stay in good network performance. These changes must be considered by the network and the development methods must be adopted to deal with them.

For establishing a realistic sensor network, we propose an innovative sensor placement approach using Voronoi-based optimization methods integrated with digital terrain and surface models. For that purpose, an optimization process is coupled to a Geographical Information System (GIS) for integrating spatial information, including man-made (buildings, bridges, etc.) or natural objects. Moreover, the functions and capabilities available in GIS serve more facilities in sensor network deployment. Visibility, line of sight and viewshed analysis are examples of GIS operations that will be used in this regard. Finally, we deploy a dynamic geometric data structure based on Voronoi diagram in order to consider the topology of the sensor network and its dynamics (e.g. inserts, move, delete). In short, our approach focuses on definition and implementation of a framework that integrates environmental information for optimal deployment of sensor nodes based on a geometric data structure (e.g., Voronoi diagram) and optimization algorithms.

A GIS aided simulation platform based on a geometric data structure is used to deploy sensors in the network and reduce the uncovered areas. A GIS is applied to define spatial positions and topological relations of environmental objects such as buildings, vegetation, and sensor nodes in different layers. It also uses other environmental information such as Digital Surface Models (DSM) to get more reliable results. DSMs are very important issues to be included in the realistic modeling of sensor placement, which have been less considered in most of the previous works. Using GIS also helps the deployment process in terms of analyzing the visibility between the sensors (viewshed) and line of sight for sensing area of each sensor in the network.

The proposed framework consists of three major parts including a spatial database (GIS), a knowledgebase and a simulation engine, based on Voronoi diagram (Figure 3.12). The spatial database is implemented using a GIS, where different environmental elements are organized as different layers, such as man-made and natural obstacles (e.g., streets, building blocks, trees, poles and terrain topography). Another layer contains the network coverage, which is calculated in different steps of the sensor network placement process. The next layer would be the layer of sensors positions. These various GIS layers may be updated during the sensing mission considering this fact that the coverage layer may be changed following changes in the environmental information layers or sensor node positions. The network and spatial environment attributes are defined in different layers that constitute the database. Different metric and topologic operations are then exported based on the analyses that are carried out here such as visibility and viewshed analyses.

The second component is the knowledgebase. All mentioned environmental and network parameters that made the GIS database are integrated to a knowledgebase that is used to extract the deployment rules and actions. Then, the knowledgebase is applied to a reasoning engine for sensor network deployment. The reasoning engine consists of the extracted deployment rules and facts as well as a local optimization algorithm based on Voronoi diagram. It generates appropriate commands to move sensors inside the network to satisfy the desired coverage level. In fact, the optimization algorithm tries to relocate the sensors based on extracted rules in the knowledgebase. Both the database and the knowledgebase components are in relation with the simulation engine as shown in the Figure 3.12. These concepts are explained in more details at Chapter 4, when the concept of contextual information and context-aware deployment optimization are introduced.

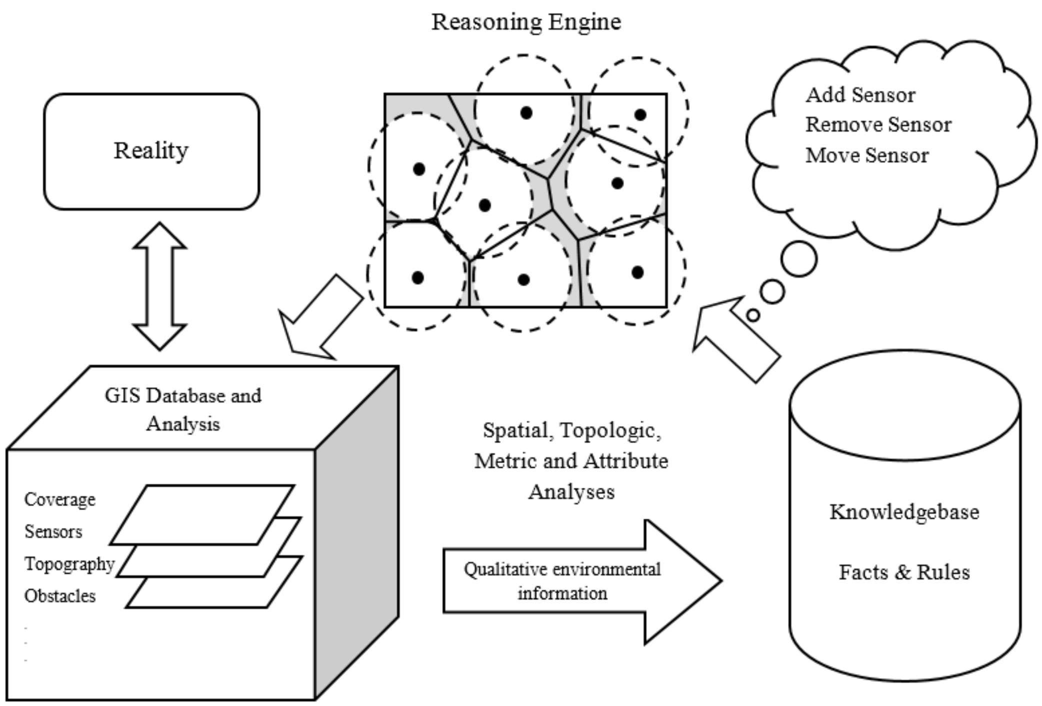
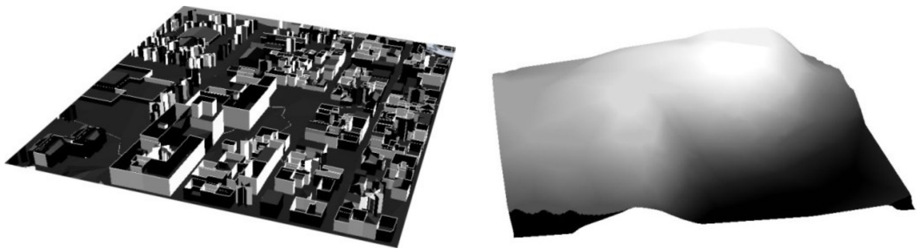


Figure 3.12: The proposed framework

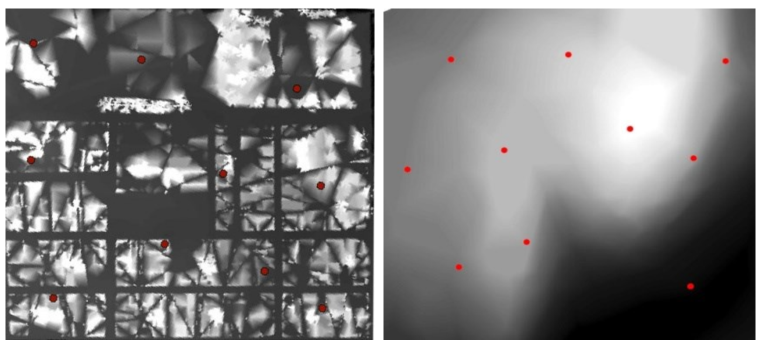
3.7 Implementation of the proposed Approach for Two case Studies

For evaluation purpose, the proposed sensor deployment approach has been used in two case studies. The first case consists on deploying a sensor network in an urban area, which is a small part of Quebec City (Figure 3.13a). In the second case study, we consider a sensor network in a natural area in a small part of Montmorency Forest located in the north of Quebec City (Figure 3.13b). Initially, the study areas were covered by 10 sensors with a sensing range of 50 meters for both cases. The sensors can rotate -90º to 90º vertically and 0º to 360º horizontally. Initially, the sensors were considered to be randomly distributed in both the natural and urban study area. For the urban data set, we suppose that the sensors are deployed in a network to monitor activities in a small part of a city. Assuming this, the sensors could be video cameras or optic sensors with the ability to rotate in 2D or 3D orientations, installed a few meters above the ground. This assumption is necessary to better consider the presence of different obstacles in the sensing area.



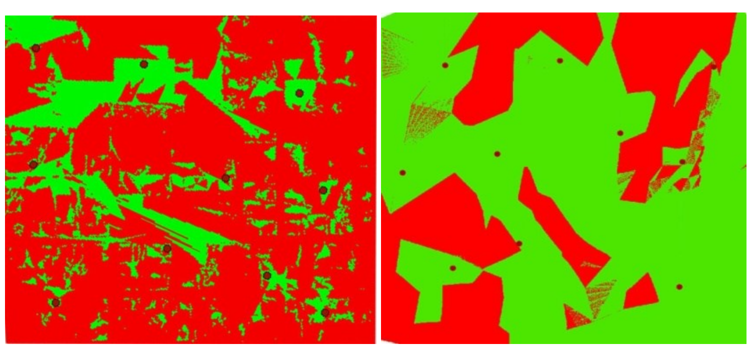
(a) (b)

Figure 3.13: The study areas: (a) a small part of Quebec City (urban area) and (b) a small part of Montmorency Forest in Quebec (natural area)



(a) (b)

Figure 3.14: Initial positions of the sensors on the DTM: (a) urban area (b) natural area



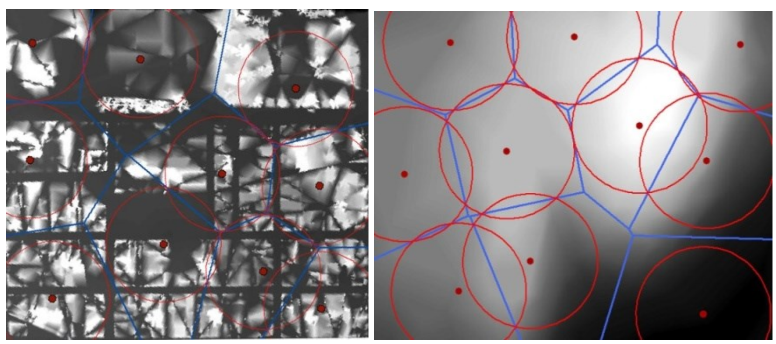
(a) (b)

Figure 3.15: Viewshed of the first sensor deployment: (a) urban area (b) natural area. Green regions are visible and red regions are invisible.

Figure 3.14a and 3.14b show the initial position of the sensors on the DTM, of the urban and natural areas respectively, which result in viewsheds of the sensors in the environments

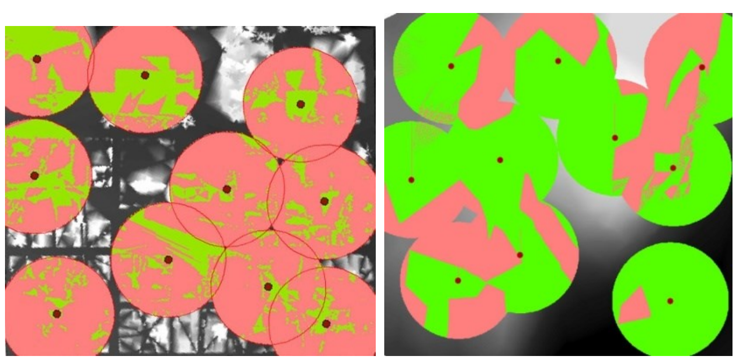
(Figure 3.15a and 3.15b).A pixel is assumed to be visible if it is observable by at least one sensor.

A 50-meters buffer around each sensor shows its sensing range. As explained in section 3.5, it is desired that each sensor node cover its Voronoi cell. Therefore, as shown in Figure 3.16a and 3.16b, the current configuration is not optimal because there are areas that are covered by none of the sensors. Overlaying the buffers and the viewshed maps, the visible area in the sensing field of each sensor node is obtained (Figure 3.17a and 3.17b), which is 23% for the initial deployment of the sensors in the urban area and 66% in the natural area. We called this overlaid area, the coverage of each sensor. While, the visibility means all of the area, which has the possibility to be observed by the sensor nodes without considering the sensing range of the sensors.



(a) (b)

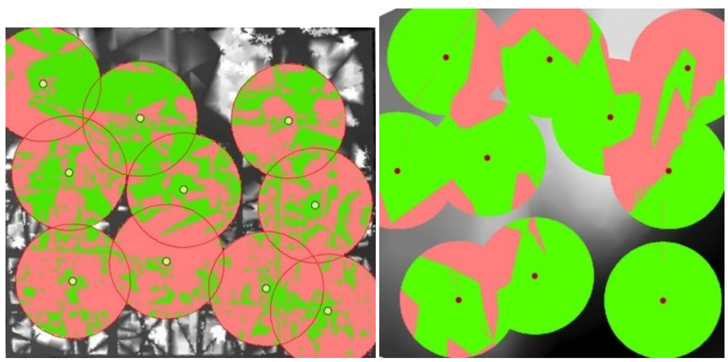
Figure 3.16: Sensor's positions and their related sensing buffer and Voronoi cells in the initial deployment: (a) urban area (b) natural area



(a) (b)

Figure 3.17: The covered regions in the sensing field of each sensor node in initial deployment: (a) urban area (b) natural area. Green regions are visible and pink regions are invisible.

To increase the covered area, the VOR algorithm (Section 3.5) is used: the sensors were moved toward the farthest Voronoi vertex, but with this restriction that the sensor stops if it reaches a position with a higher elevation than its current position. This constraint is an extension to the VOR algorithm that allows us to better consider the topography of the terrain and the presence of various obstacles in the sensing area. This consideration helps to significantly improve the spatial coverage of the sensor network in both case studies and also prove our initial hypothesis. Figure 3.17a and 3.17b show the result of this movement. As Table 3.1 indicates, both of visibility and coverage have been relatively improved in both urban and natural areas. In urban area, the visibility has been increased 12% and 4% in natural area. In terms of coverage, in urban area there is 14% of coverage improvement and in natural area we can see 5% of coverage improvement.



(a) (b)

Figure 3.18: The covered regions in the sensing field of each sensor node in second deployment (green regions are visible and pink regions are invisible)

Table 3.1: Visibility and coverage before and after optimization

Case		Visibility (no. of pixels)	Visibility (%)	Coverage (no. of pixels)	Coverage (%)
Urban area	Before optimization	23458	22	16810	23
	After optimization	37463	34	25174	37
Natural area	Before optimization	60250	67	40806	66
	After optimization	63995	71	43952	71

3.8 Discussion and Conclusions

This paper was focused on the coverage problem of geosensor networks. First, we have presented an overall review of the existing approaches for the optimization of the coverage of geosensor networks. Especially, algorithms that use Voronoi diagram and Delaunay triangulation were intensively investigated. As discussed in the paper, most of these methods oversimplify the coverage problem and they do not consider the characteristics of the environment where they are deployed. Spatial coverage of sensor networks is related to the spatial distribution of the sensors in the environment. The coverage determination algorithms try to distribute the sensors in the field so that the maximum coverage is obtained.

Voronoi diagram and Delaunay triangulation are well adapted for abstraction and modeling of sensor networks and spatial data structures. They are also frequently used in this area. However, their application is still limited when it comes to the determination and optimization of spatial coverage of more complex sensor networks (e.g., sensor networks with the presence of obstacles).

To overcome the limitation of these methods, a novel approach based on Voronoi diagram has been proposed which considers spatial information in senor network deployment and coverage optimization. In order to evaluate the proposed method, two case studies were presented in the paper which present and compare the sensor network deployment and its spatial coverage both in urban and natural areas. The preliminary results obtained from these experimentations are very promising. As presented in the last section, we have observed a considerable improvement in the spatial coverage of the geosensor networks in both cases. These results are a part of an ongoing research project and more investigations will be carried out in order to improve the quality and the performance of the proposed method in the future.

3.9 Acknowledgment

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CHAPTER 4

Context-Aware Local Optimization of Sensor Network Deployment

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4.1 Abstract

Wireless sensor networks are increasingly used for tracking and monitoring dynamic phenomena in urban and natural areas. Spatial coverage is an important issue in sensor networks in order to fulfill the needs of sensing applications. Optimization methods are widely used to efficiently distribute sensor nodes in the network to achieve a desired level of coverage. Most of the existing algorithms do not consider the characteristics of real environment in optimization process. In this paper, we propose the integration of contextual information in optimization algorithms to improve sensor networks coverage. First, we investigate the implication of contextual information in sensor network. Then, a conceptual framework for local context-aware sensor network deployment optimization method is introduced and related algorithms are presented in details. Finally, several experiments are carried out to evaluate the quality of the proposed method. The results obtained from these experiments show the effectiveness of our approach in different contextual situations.

4.2 Introduction

Wireless sensor networks are increasingly used for environment and habitat monitoring, moving objects tracking, transportation, structure monitoring, temperature and humidity control, etc. The application of sensors have dramatically improved data collection from the environment and made it easier, cheaper, and more effective.

In order to better understand and capture a dynamic phenomenon by the sensors, effective coverage of the environment is critical. Sensor network deployment optimization approaches are developed to help to achieve this goal. There are different approaches for deployment of sensors in the environment. Random scattering and regular grid-like distribution methods are examples of sensor deployment strategies. Manual deployment is one of the simplest ways, but it does not completely satisfy all the requirements of sensor network deployment missions, like providing optimum visibility of objects inside the network. Moreover, regular or random spreading of sensors uniformly in environments may provide a coverage that does not adequately satisfy the user's needs.

Sensor network deployment consists in determining which sensor, where, and how it should be installed (e.g. sensor type, position, orientation) in the environment, in order to monitor a given region of interest according to the initial consumptions. A way to achieve this, is to use optimization algorithms for maximizing a given coverage function of the sensor networks in the environment, for automatically determining the positions and orientations of the sensors. Spatial coverage of sensor networks has different definitions based on different applications (Aziz et al. 2009; Ahmed et al. 2005; Ghosh & Das 2008; Huang & Tseng 2005; Megerian et al. 2005; Meguerdichian et al. 2001; Loscrí et al. 2014). The visual coverage of a point in the environment by a sensor network means that the point is directly visible by at least one sensor and is located within its sensing range. Failing to meet this condition produces some visual holes in the desired network coverage (Ahmed et al. 2005). Many parameters exist, which directly affect the coverage of a sensor network, for example, relations and interactions among sensors in the network, between sensors and environmental elements, and among the environmental elements themselves. Hence, awareness of the surrounding information may help network coverage optimization by means of sensor deployment. In this paper, such knowledge are introduced, and called Contextual Information (CI).

So far, most sensor deployment research uses simplistic approaches and does not consider the real spatial entities composing the environment. For example, Wang et al. (2006) have investigated strategies for moving mobile sensors to positions where the required coverage is attained, without explicitly considering the forms of CI available in the real environment, such as terrain topography, obstacles, and environmental objects. Further, relations among spatial elements are necessary to be considered in sensor deployment, for example, connectivity, adjacency, inclusion, and exclusion of environmental elements. Thai et al. (2008) have also addressed sensor deployment, where coverage formulation and analysis solutions for sensor deployment have been introduced with less consideration to the terrain analysis of the real spatial elements.

In this paper, the concept of CI is investigated by considering several categories of context in specific case studies of sensor network deployment. A conceptual framework for context-aware sensor network deployment is introduced in order to improve coverage inside the network based on some initial assumptions. The proposed framework considers network and environment elements, their dependencies, and characteristics, and applies mentioned CI over the sensor deployment. Hence, in order to improve the coverage, different rules are concluded based on introduced CI to perform different actions such as moving existing sensors, or adding new sensors. Afterward, a local optimization algorithm is developed based on the proposed framework, which locally optimizes the sensor positions by considering the coverage gain improvement of each sensor movement.

The rest of paper is organized as follows. Section 4.3 briefly reviews optimization algorithms for sensor network deployment. The concept of context in sensor network is introduced in Section 4.4, followed by discussions on context-aware sensor network deployment. In Section 4.5, a conceptual framework for sensor placement based on Voronoi diagram and contextual information is introduced. Section 4.6 presents the proposed local optimization algorithm in detail, along with experimentation results in Section 4.7. The paper concludes in Section 4.8 with results highlights, summary of the proposed approach, and possible future developments.

4.3 Optimization Algorithms for Sensor Networks Deployment

Efficient sensor deployment is an important issue for exploitation of sensor networks, due to its effect on coverage and communications between the sensors in a network. There are a variety of coverage formulations in the literature depending on the type of coverage needed (e.g., area, points, barrier), the sensor deployment mechanism used (e.g., random or deterministic deployment), and the requested properties of sensor networks (e.g., network connectivity, minimum energy consumption) (Cardei & Wu 2004). In this study, the authors consider the coverage as blanket coverage and sensors as visual cameras. Blanket coverage requires placing a minimum number of nodes in an environment, such that every point of interest in the sensing area shall be adequately covered regarding tasks at hand (Aziz et al. 2009; Ghosh & Das 2008). Optimization algorithms define how a good placement is achieved (Zou et al. 2003; Ghosh & Das 2008; Niewiadomska-Szynkiewicz & Marks 2009; Romoozi & Ebrahimpour-komleh 2010; Argany et al. 2011; Argany et al. 2012; Akbarzadeh et al. 2013; Loscrí et al. 2012; Erdelj et al. 2013). These approaches are generally categorized into global and local optimization methods (Argany et al. 2012). Both categories are intended to give the best blanket coverage, but the way each method achieve this objective is different. Global approaches consider the whole physical space to find the desired coverage within the network, while local optimization methods try to find the answer based on some local considerations such as network topology and spatial analysis. On the other hand, local approaches divide the search space into local spaces and search the answer locally. In this study, position of each sensor is determined based on local coverage improvement. The spatial coverage of a sensor network in global and local models depends both on the spatial distribution of the nodes and the spatial information of the environment embedding the sensor network. This information defines CI that will be involved in our sensor network deployment approach.

Here a new local context aware optimization algorithm is proposed to address some limitations of the existing methods. The algorithm uses the Voronoi diagram in order to model the topology of the network and locally take into account the spatial information of the environmental elements. In the following sections the concept of the "context" and its implications for intelligent deployment of sensors will be defined in detail. Afterward, based on this definition a conceptual framework for local context aware sensor network deployment and a related optimization algorithm is presented.

4.4 The Concept of Context in Sensor Networks

The concept of context is extensively studied in the literature. According to the Oxford Dictionary, a context is the "circumstances that form the setting for an event, statement or idea, and in terms of which it can be fully understood and assessed." In some studies, not specifically on sensor networks, context has been introduced as locations, identities of the people or objects around a user, or subjects related to the time like time of the day, week, or season (Brown et al. 1997; Ryan et al. 1998; Dey 1998; Schilits & Theimer 1994). All of these definitions consider context as the situation of the specific object or event, or the situation of an application. They look at the context regarding to the environment surrounding the specific object, or the application (Franklin & Flaschbart 1998). There are other studies considering the entire environment by defining the concept of context as the aspects of current situation (Hull 1997).

Hence, the context of an object can be defined as the answers to these questions: where the object is, whom the object is with, and what resources are nearby. In this definition, the concept of context is related to the state of the environment and may be changed when that state is changing. Dey et al. (2001) recommend three aspects to be considered in the environment when the concept of context is defined in the field of computer applications: the computing environment, the object environment, and the physical environment. Computing environment addresses the available processors, storage, input and display devices accessible for object, network capacity and connectivity, while object environment concerns the location, behavior, and neighbors of the desired object of the context-aware analysis. Physical environment constitutes the physical characteristic of the study area.

In order to provide a meaningful definition for the concept of "context" in sensor network deployment domain of application, the concept of sensor shall take the role of the main object of interest in such a definition. Here, as formalized in Figure 4.1, the main object of interest for which we attempt to define a context is a sensor. Sensor network is considered as the object environment, which includes information on the sensors, for example, physical components of the sensors, the sensors position, the types of sensor movement, or the spatial relations between sensors in the network. Physical environment is composed of spatial objects in a given area in which the sensor is placed. It also may refer to the spatial relations among the objects, the specific locations in the environment such as desirable areas to be covered or restricted positions that are forbidden to set up the network (Figure 4.1).

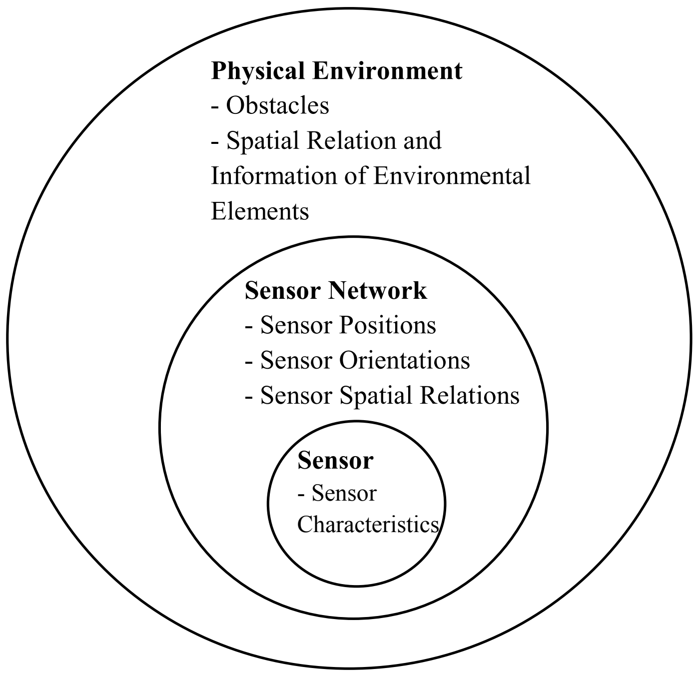

Figure 4.1: Three components of context in sensor network deployment

In sensor network deployment, the context definition may consist of the sensor network's preferences, objectives, and interests. Considering these terms, an intelligent sensor network deployment method is defined (Figure 4.2). Therefore, a comprehensive definition of context for sensor networks deployment is introduced as:

Context is the whole situation, background, or environment of a sensor network. It includes information on sensor itself, the network, and the physical environment and their interactions in a given time.

Using this definition in sensor network, Contextual Information (CI) is defined as the information of sensors, sensors network and the physical environment and spatiotemporal relationships exists among these elements. That being said, CI in sensor networks deployment consists of spatial dependencies and interactions between the nodes inside the network as well as temporal reactions, movement, and characteristics of the same nodes' information. It also results in actions, which enable the sensors to locally predict their positions and being aware of both temporal information and the current situation of themselves and their neighbors.

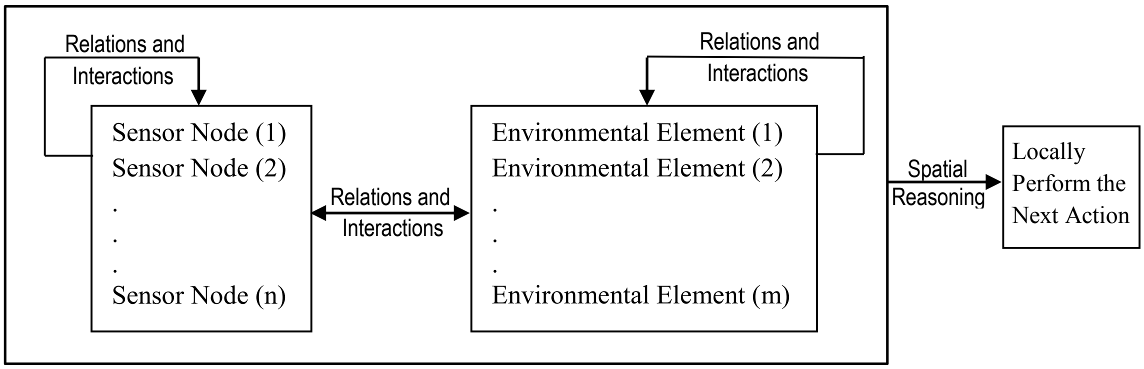

Figure 4.2: Context definition for the intelligent sensor deployment for a given time

4.5 A conceptual Framework for Sensor Network Deployment Using Voronoi Diagram and Contextual Information

In this section, a conceptual framework of sensor network deployment is proposed that applies the introduced contextual information. As explained in Section 4.3, many optimization algorithms have been used in coverage optimization of sensor network deployment. Some of these algorithms, such as solutions proposed to the Art Gallery problem (Shermer n.d.), relies on strong assumptions and considers only a specific element of the environment (e.g., the walls of an indoor environment). Some others, such as derivative-free black-box optimization methods, are not considering explicitly the environmental information, spatial location, and objects around the sensors, although these can be included implicitly in the merit function guiding the optimization. According to Section 4.4, there are various pieces of information available in each sensor network environment to be considered by the optimization algorithms. The so-called CI will be used in the proposed framework to find good candidate positions of sensor nodes, in order to guide sensor network deployment. Since sensors configuration and their spatial relations may directly impact the optimization process, Voronoi diagram is used in the conceptual framework to model the network environment. It establishes a geometric structure of sensor configuration inside the network as well as the physical environment. It also helps to detect coverage holes in the network, and healing the holes by adding new sensors or moving the existing nodes (Argany et al. 2011). A Voronoi diagram for a finite set of points in a given space (here sensors nodes) is a subdivision of the space where every location in the space is assigned to the closet member in the point set. . Given a sensor node inside each Voronoi cell, it is supposed that the cell generator (sensor nodes) covers the cell area. Since there are many parameters such as limits on sensor sensing range, and obstacles that bar the line-of-sight between the sensor and sensed objects, gaps and holes inside sensing area will appear. These holes are found by overlapping the Voronoi diagram and the sensor sensing coverage model. Consequently, the CI is included as an essential part of the framework to make it more effective at finding the holes and deciding on sensor's adequate actions. The first CI that is considered in this investigation would be the height of spatial elements inside the study area. Argany (2010) and (2011) has introduced "enhanced Voronoi-based algorithm", which used Voronoi diagram as a geometrical structure to optimize the coverage in the network by finding the appropriate positions of the sensors inside the network. The optimum positions in this method were found by moving the sensors toward their new positions by considering specific rules to heal the existing holes. The term "enhanced" in the algorithm refers to the use of information for elevation, line-of-sight, viewshed and etc. as contextual information to improve the sensor's position. Section 4.7 presents more details of CI related to different case studies presented later in in this paper.

The contextual information may be very divers in their nature and require different strategies to be categorized in terms of integration in optimization algorithms. CI in sensor network deployment could be classified into spatial, temporal, and thematic information.

- *Spatial* contextual information refers to the ability of defining objects positions, and geometric relations. Spatial CI is not only about 2D or 3D position of sensors. A comprehensive framework of spatial contextual information may include sensors orientation, movement, routing, targeting, topology, and spatial dependencies and interactions. Hence, all information of spatial relations, interactions, proximity, and adjacency lie in this category.

- *Temporal* contextual information concerns the temporal information, and the temporal dependencies in data. Temporal information characterizes the dependency of a situation in the sensor network framework with the time, and also indicates an instant or period during which some other CI is known or relevant. The objects and activities in the physical environment may change. For instance position or attributes of an obstacle (e. g. its height) may change during a given period of time. A specific example of temporal CI is the information of a sensor movement and its trajectory in the network. Previous actions and movements of a sensor node may provide useful information for the next actions of current sensor or its neighbors.
- *Thematic* contextual information in sensor networks constitutes the sensor specifications, network objectives, environment specifics, legal rules, etc. The information regarding the nodes names and roles, and their activity in the network is included in this category. Sensors activities may include measurement of the temperature, humidity, sound, or light. In terms of deployment, the type of sensor movement and its trajectory could be the sensor activity inside the network. Node name should be unique in the network in order to make it possible to be recognized and devolve its roles in multi tasks networks. Sensor characteristics are sensor specifications, which have been designed during their manufacturing, e.g., their power supply, battery life, sensing range, temperature resistance, dimensions, input and output terminals, processing power, data storage capacity, send and receive information protocols, and etc. Network objective express the mission of sensor network to be fulfilled. This objective could be various in multi task networks. It may be varied from covering a whole, or a part of study area to monitor a phenomenon, or sensing different characteristics of the environment. Legal rules define specified terms and conditions for constructing and deploying the sensor networks, e.g., in which locations sensor deployment is allowed, or which parameters are permissible to be measured.

Figure 4.3 presents our proposed context-aware sensor network deployment conceptual framework. The proposed frame work has several main components. In the first module, the appropriate CI is extracted from the real world based on tasks at hand. After introducing the CI to the framework, two databases of physical and network environments are created. The spatial database of physical environment includes information of spatial entities such as obstacles, surface elevation and information about restricted areas; while the network database comprises the CI related to sensors and their relations, such as vicinity and topology information provided by Voronoi diagram. The next component is a knowledgebase. The knowledgebase is derived from both databases that provide the necessary knowledge about the sensors, the network and its surrounding environment. This knowledge is provided to the optimization algorithm to better perform the deployment decisions. In the next step, a reasoning engine is applied using the predefined knowledgebase. The reasoning engine may use different move strategies to decide how and in which direction sensors will be displaced (extracted rules). In this work, the reasoning engine is a component of the proposed optimization algorithm, which uses the provided knowledge and information to make a decision on actions to deploy sensors in the environment regarding the initial considerations. In fact, the appropriate actions in the form of extracted rules will be applied. These rules may contain different deployment strategies. For example, suppose that there are some places in the study area with high interest of coverage, but prohibition of sensor installation. Hence, the reasoning engine extract two rules: move sensors toward the regions with high interest of being covered and increase coverage in those areas as much as possible, while preventing sensors to be entered those areas. Therefore, the reasoning engine inside the optimization algorithm may change the deployment process based on provided local contextual information.

These actions may change the topology of the network, the configuration of the adjacent nodes, and consequently, the local coverage. Following each action, local CI of the sensor and its neighbors need to be updated. Hence, some facts and rules may change in the knowledgebase. These local actions carried out iteratively until a desired level of coverage is reached in the network. The process of local optimization in the framework means that network configuration is changed step by step until it obtains its desire configuration considering the spatial, temporal, and thematic contextual information in the network (Figure 4.3).

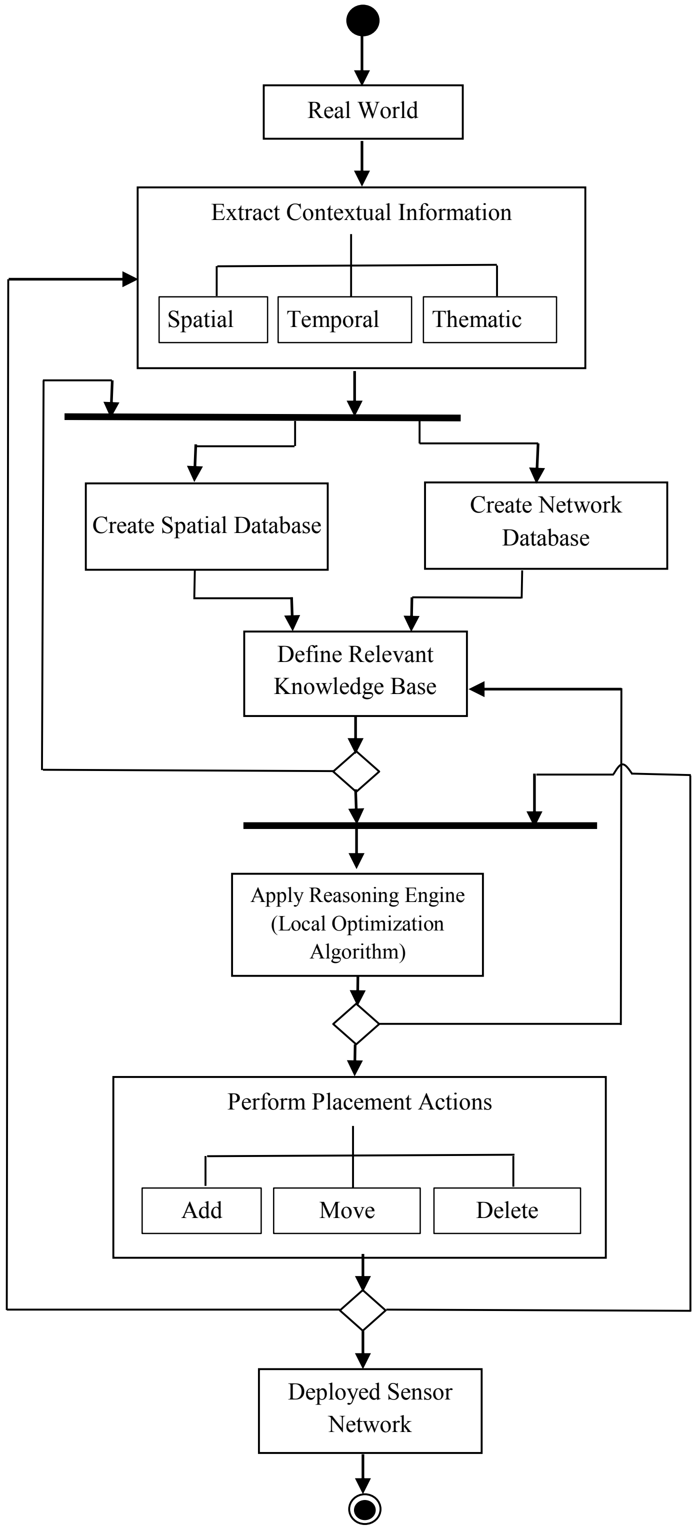

Figure 4.3: Context-aware sensor network deployment framework

4.6 Implemented Local Context-Aware Optimization Method for Sensor Placement

According to the proposed framework for sensor network deployment, a local optimization algorithm is developed to tackle the sensor placement problem and maximize the spatial coverage of the network. The algorithm utilizes the Voronoi diagram to model the network spatial structure. Here we propose a generic algorithm to optimize sensor deployment by means of considering local CI to define sensors actions such as movement, deletion, and insertion within the network. The types of CI and their related sensor behavior may be different and are customized according to a sensor network deployment task at hand. Some examples of specific local CI used in some case studies will be introduced and discussed later in Section 4.7.

4.6.1 Formal Presentation of the Local Context-Aware Algorithm

In this section, the proposed algorithm is described in more formal perspective. As illustrated in pseudo-code presented in Figure 4.4, at the first step of the algorithm, a set of sensors $S = \{s_1, \ldots, s_n\}$ is deployed randomly in the network. These sensors are then considered as the generators of the Voronoi diagram. Next, the related coverage of each sensor at its initial position is calculated (*coverage(s_i)*). Meanwhile, different types of coverage may be assumed, which is customized according to the network deployment task at hand. In this study its simplest form, blanket coverage (Ghosh & Das 2006) is used.

The next step consists of defining the set of context-aware actions (move, add, or delete a sensor) to be considered during the optimization. Section 4.7 explains how these context-aware actions are defined (Here, for the sake of simplicity, we consider the move action) Next, each possible action is simulated, and local coverage value of each sensor in the network is recalculated:

$$c_i = \text{coverage}(\text{move}(s_i, S)), \forall s_i \in S.$$

Any local move changes the local coverage of a sensor. As a result, the global coverage of sensor network S need also to be updated. The potential gain (g_i) for each move is computed as follows:

$$g_i = \text{coverage}(\text{move}(s_i, S)) - \text{coverage}(s_i, S), \forall s_i \in S.$$

In this step, a greedy algorithm is applied to order the sensors in a priority queue, which means that a simulation of movement has been conducted for all sensors before their permanent move. Sensors are sorted in the priority queue based on their coverage gain following respective simulated moves in the network. Next, the sensor with the best global coverage gain is selected to move locally. Accordingly, for each step, the algorithm is looking for the sensor move with the highest coverage gain based on local CI in the network. Then, s_u' the new position of the selected sensor (s_u) will be computed regarding the defined context-aware move:

$$s_u' = move\ (s_u, S)$$

The next action is to move the selected sensor to its new position. Hence, the network configuration will be changed because of this movement, and as a result, the local adjacency of the sensors may be modified. Accordingly, the set of neighboring sensors of the moved sensor should be determined in the next step. That neighborhood allows updating the coverage values of each adjacent sensor in the priority queue that might be affected by the movement of a sensor. The update operation is then a local operation and hence we do not need to update all the sensors following a local move in the network. Here, two sensors are considered to be adjacent if their respective Voronoi cells are contiguous. It should be noted that if the distance between two neighboring sensor nodes is less than two times of the sensing range, then a part of sensing area will be covered by the both sensors between them. Multiple coverage can be introduced and managed as a CI if required. Here we suppose that each point in the space is covered only by a single sensor.

Next, the sensor with the best coverage gain will be moved. These steps will be run iteratively as long as maximum coverage gain of sensors in the network is greater than a predefined coverage gain threshold (ε).

Variables:

- $S = \{s_1, s_2, \ldots, s_n\}$: set of sensor positions making the sensor network
- g_i : coverage gain offered by the move of sensor s_i
- ε : coverage gain threshold before stopping the optimization
- CI: set of contextual information

Functions:

- $c = \text{coverage}(s_i, S)$: compute coverage of sensor s_i in network S
- $s_i' = \text{move}(s_i, S)$: apply the move to sensor s_i in the network S

Algorithm:

1: Initialize the sensor positions in the network, $S = \{s_1, \ldots, s_n\}$

2: Define the sensor movement based on the CI set

3: Compute potential gains for all sensors following their first move,

$$g_i = \text{coverage}(\text{move}(s_i, S)) - \text{coverage}(s_i, S), \forall s_i \in S$$

4: **While** $\max_{i \in S} g_i > \varepsilon$ **do**

5: Select the sensor with the highest global coverage gain,

$$u = \arg\max_{i \in S} g_i$$

6: Compute the new position of the selected sensor, $s_u' = \text{move}(s_u, S)$

7: Move the selected sensor to its new position,

$$S = \{s_1, \ldots, s_{u-1}, s_u', s_{u+1}, \ldots, s_n\}$$

8: Determine the set of neighboring sensors of the moved senor,

9: Evaluate and update the new potential gain in coverage of the neighboring sensors of s_u',

10: **end while**

11: **return** S

Figure 4.4: The pseudo-code of the proposed local context-aware optimization algorithm

Figure 4.5 presents a simplified scenario for a few moves usingof the proposed local context-aware algorithm execution for deploying 5 sensors in a flat environment. Red vectors in the figure represent the move direction of the sensor with top priority in each step. In Figure 4.5a, the sensor in the Voronoi cell A gets the highest rank to move. It may seem that sensor at cell E has the priority to move because of more uncovered space in that cell, but its movement does not have significant impact on coverage gain since the circular sensing area is displaced inside the cell, while the uncovered area will almost remain the same. In Figure 4.5b, the sensor in the Voronoi cell D is selected to move due to the greater area that will be covered compared to other cells, as well as cell B in Figure 4.5c. In Figure 4.5d, the sensor inside the cell A has been selected again to move. During this simulation, sensors at cells C and E never get the highest priority to move. This means that the coverage gains of these sensors are always less than the other sensors through this round of optimization. As explained, in cell E there is no overlap between the sensing regions of this sensor and its neighboring sensor cells, then its movement does not have significant impact on the coverage of the network. Sensor at cell C does not get the priority to move, since its cell has been already well covered. A comparison between Figures 4.5a and 4.5d show that at the end of this round of simulation, the global coverage in the network has been improved.

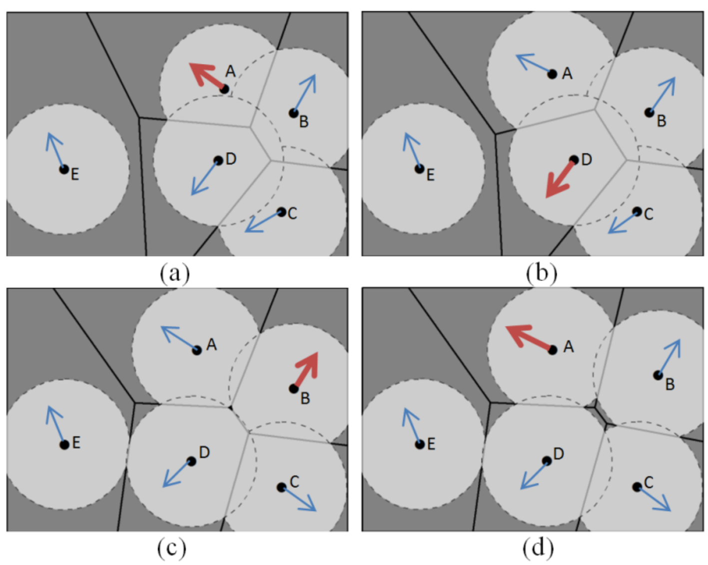

Figure 4.5: Simplified simulation of one round of the proposed algorithm to deploy five sensors. Red vector represents the move direction of the sensor with best priority to move in each step.

4.6.2 Strategies for Sensor Movement in the Proposed Local Optimization Algorithm

As stated in the previous sections, different actions are proposed for optimization process depending on local context information for each sensor. These actions may include addition, deletion and movement of a sensor in the network. Moving a sensor is one of the important actions for sensor network optimization. Each move in the proposed deployment optimization approach is composed of two parameters: moving distance and moving direction. Moving distance is determined using a set of rules by the reasoning engine. These rules are defined and stored in the knowledgebase (for more details please refer to the Section 4.7). Orientation of movement is defined based on simple Voronoi diagram.

Before explaining our strategy for determination of moving orientation we recall the definition of a simple Voronoi diagram. Given a set of two or more finite distinct points in the Euclidean plane, each location is associated in that space with its closest member(s) of the point set with respect to the Euclidean distance. The result is a tessellation of the plane into a set of regions associated with individual members of the point set. This tessellation is called simple "Voronoi diagram" generated by the point set. The regions constituting the Voronoi diagram are referred to as "Voronoi cells". From the mathematical point of view, consider a finite number of *n* points in the Euclidean plane with location vector x_i for $i \in \{1,\ldots,n\}$ where all the points are distinct ($x_i \neq x_j$ for $i \neq j$ and $i, j \in \{1,\ldots,n\}$). Now, let consider an arbitrary point p in the Euclidean plane with position vector x, the Voronoi polygon of point p_i is given by:

$$V(p_i) = \left\{x \middle| \| x - x_i \| \leq \| x - x_j \| \text{ for } j \neq i, j \in \{1,\ldots,n\}\right\}$$

For a sensor network, a Voronoi diagram is constructed using initial locations of the sensors. Each sensor in the network is considered as the generator of a cell in the Voronoi diagram, and is responsible for covering the area of its Voronoi cell in the network. In this study, the sensing range for each sensor is considered as a disk with a given radius *r* around a sensor. Given the circular covered area, and the Voronoi cell of a sensor node, the uncovered area is defined as the symmetric difference of the Voronoi cell and the sensing disk (Figure 4.6).

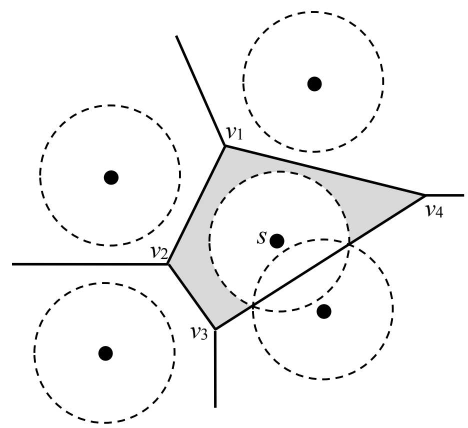

Figure 4.6: Voronoi diagram for five sensors in a network. Dashed circles represent the sensing area of each sensor; the gray region represents the uncovered area of the Voronoi cell associated to the sensor s.

Suppose that a sensor with a circular sensing area is located at point p_i, and it does not cover $V(p_i)$ completely. Then some uncovered area within the Voronoi cell exists. In this situation, there are some strategies to heal the holes (Argany et al. 2011). Moving the sensor may improve the coverage inside the $V(p_i)$, and hence, the global coverage over the network.

The most probable uncovered area inside a Voronoi cell might be in the direction of the farthest Voronoi vertex from the sensor position that generates the cell (Wang et al. 2007; Argany et al. 2011). Hence, the reasoning engine in optimization algorithm uses different move strategyies to decide how and in which direction sensors will be moved (extracted rules). The strategy that is used in the proposed algorithm is to move toward the farthest Voronoi vertex on the line $\overline{s_i v_{farthest}}$. Thus, for each sensor, an increase of its coverage is expected if the sensor move will be directed toward the farthest vertex in its Voronoi cell. The proposed move may change its direction or distance at each step based on new CI. After each move of a sensor, configuration of the network is changed. Hence, the Voronoi diagram of the network is modified and the adjacency of the moved sensor is updated. That being said, the trajectory of a sensor may not be linear during the optimization process, which means that sensor movements are changed during the iterations, and the improved direction and distance are applied (Figure 4.7).

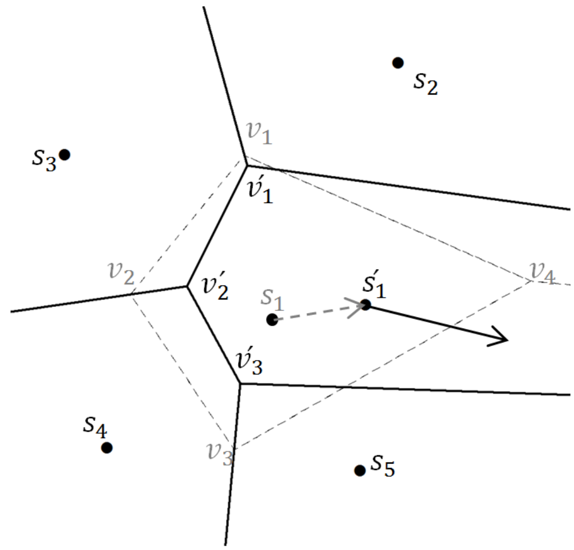

Figure 4.7: Moving direction and distance changes during the optimization process, dashed line represents the first step of the optimization, and solid line the second.

4.6.3 Strategies for CI Integration in the Proposed Local Optimization Algorithm

In the proposed local context-aware optimization algorithm, different actions including addition, move or deletion of a sensor are defined based on local contextual information. Depending on the nature of CI different strategies may be applied to carry out these actions. In most cases, it is possible to map spatial contextual information and manage them based on a layer based approach. For other types of contextual information, we need to have different strategy.

For spatial contextual information that can be mapped, two steps are considered for their integration in optimization process:

First, some CI categories are simulated in different layers as the raster weighted maps. For example, the CI of elevation of environmental elements is represented by a raster map that its pixel values contain the elevation. In another case, the CI of restricted area is represented by a weighted raster map with the values of zero for restricted and one for authorized regions. Therefore, the idea here is to represent different CI with different weighted raster maps. In the next section, other examples will be discussed.

In the second step, these raster layers need to be overlaid in the knowledgebase to extract appropriate rules. In order to consider different CI layers, a scoring method is used in our proposed algorithm. For example, suppose that there are two types of CI that represent the desirability of coverage for a specific area and another represents the restriction of installing sensor inside that area. Hence, we have two raster maps with two types of weights. The scoring machine overlaid these two weights and gives one score for each pixel. Then, the reasoning engine in the algorithm use these scores to extract the optimization rules and decide how and in which direction sensors will be moved inside the network. These two steps will be more clarified in next section when different case studies are presented.

There are other types of CI were presented in Section 4.5, that can not be integrated in the proposed algorithm by the weighted raster maps. Information on sensing range and sensing orientation of each sensor in the network are in this category. These CI are managed as introduced facts in the knowledgebase that used in optimization process. The reasoning engine considers these types of CI and integrates them to other local CI during the optimization process.in the algorithm by entering their direct values As an example; distance between neighboring sensors are computed locally at each step. This information is used as CI to avoid coverage overlap between these sensors. The rule that uses this information indicates to the system that if the distance between two sensors is less than sum of their sensing ranges, then these sensors should be moved away from each other.

4.7 Different Case Studies for Evaluation of the Proposed Local Context-Aware Sensor Network Deployment Optimization Algorithm

In this section we present several experiments that demonstrate the capacity of the proposed algorithm to consider different types of CI for sensor network optimization. The study area for our experiments is a part of old Quebec City with a dimension of 180 m by 170 m (Figure 4.8).

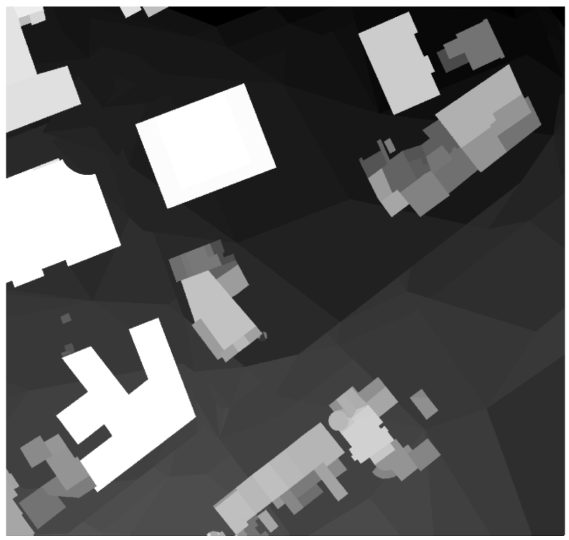

Figure 4.8: The study area of experiments

For the experiments, 12 sensors have been assumed to be deployed. The sensors are supposed to be visual cameras with 360 degrees horizontal, ±90 degrees vertical sensing angle, and 35 meters of effective sensing range. Placing sensors on the vertices of a triangular lattice is well-known as an optimal solution of deploying sensors over a flat plane (Bai & Lai n.d.). Thus, the initial positions of the sensors were defined on the vertices of a triangular lattice for all different case studies (Figure 4.9). In one situation, the number of sensors has been increased in order to find the optimal number of sensors needed to cover the entire study region.

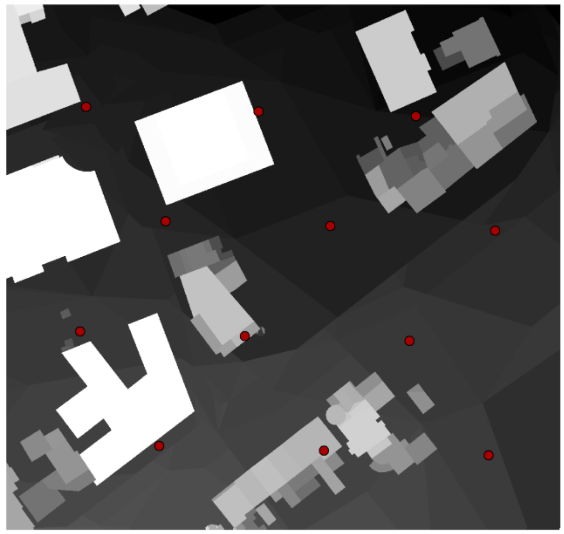

Figure 4.9: The initial positions of sensors based on a triangular configuration

For these experiments, we assume that sensors are deployed in an environment with the following considerations that constitute a part of our CI set for the experiments:

- Spatial positions of environmental elements and obstacles are known,
- Digital Surface Model (DSM) of the environment is provided,
- For each sensor, visible and invisible areas are recognized by calculation of line-of-sight and viewshed,
- Some restricted zones for sensor installation exist in the study area,
- There is a zone with high desirability of coverage, with prohibition for sensor installation,
- There is a zone with low level of activity, and high desirability of coverage. This zone is located close to a zone with high level of activity but low desirability of coverage. In both zones sensor installation is forbidden.

This CI set will be integrated to the deployment optimization process and will define the way each sensor move locally during the optimization process.

4.7.1 Optimization Considering the Obstacles and Surface Model as CI

The first category of CI to be considered in deployment optimization knowledgebase is the surface model of the network. Having this knowledge the elevation details of the study area is provided as well as the obstacles bared the sensing field of the sensors. As mentioned in Section 4.6.2, the second parameter in a sensor movement is the distance. Here, the sensor is moved toward the farthest Voronoi vertex until it reaches the highest elevation on the line $\overline{s_i v_{farthest}}$. Hence, objects elevation is considered as spatial CI in the deployment optimization. It is expected that points with the highest elevation provide better coverage compared to points at lower elevation. This CI has been used also in another part of the algorithm, when the viewshed is used to calculate the coverage in the network and consider the obstacles.

As mentioned earlier, we considered 12 sensors to be deployed on the map of old Quebec City using the proposed context-aware optimization algorithm. Figure 4.10 depicts the movement of sensors for 8 iterations. The arrows show the movements distance and direction, and the numbers beside each arrow represent the iteration number. Sensors that do not have any arrows beside them have not moved during the optimization process. In this case, four sensors had the potential of improving the network coverage, by considering the mentioned situations to define their displacements. If the rests of sensors move, they do not improve the coverage adequately regarding the predefined gain threshold. Then, they have remained on their initial triangular lattice positions. This may be explained by the fact that these sensors are located on the area with little height variation, or other sensors movements have had more impact on the coverage improvement or already covered that area. For example, the move number 4 covers all area at the top of the building beside it, this movement of the other sensor at the left side of the building will not have significant impact on the coverage in that area. So, this sensor never stands at the first rank of the priority queue, and as a result it does not move.

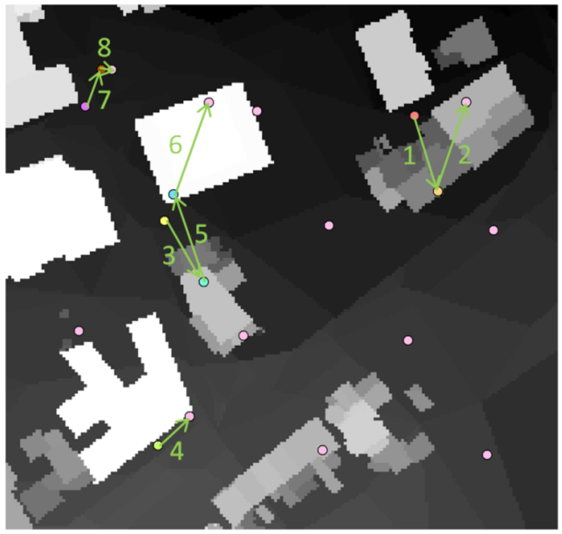

Figure 4.10: Sensor movement simulation of the context-aware optimization algorithm

Figure 4.11 depicts the coverage improvement during the optimization process related to the iterations shown in Figure 4.10. The upward slope of the diagram shows the improvement of coverage over the iterations. The initial overall coverage of the triangular lattice deployment is 58.79 percent considering the obstacles, and the final coverage obtained from the optimization is 63.46 percent. It may seem the coverage improvement was negligible. The reason of little difference between the initial and final coverage is due to the triangular lattice initial configuration, which is close to optimum (Bai & Lai n.d.). We may call the obtained coverage not only the improved coverage but also more realistic coverage due to consideration of local CI. Figure 4.12 shows the final sensor positions and covered regions.

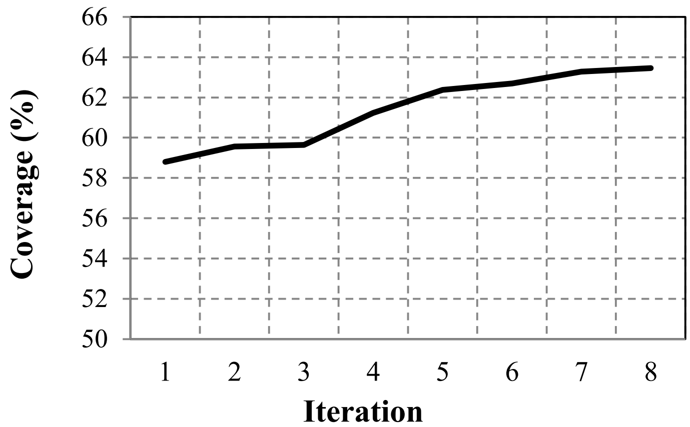

Figure 4.11: Coverage improvement over iterations of the context-aware method

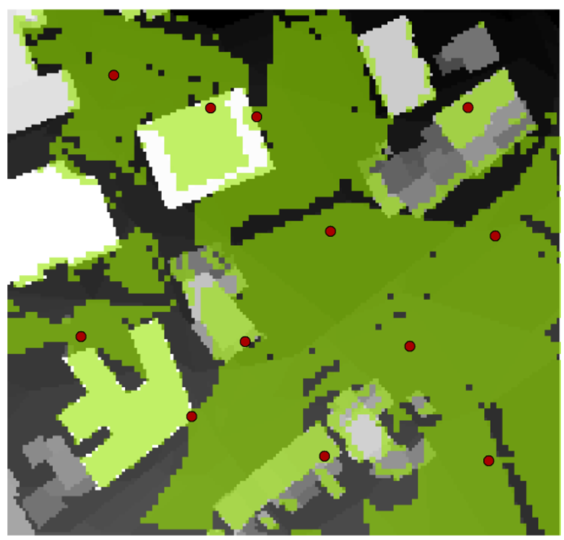

Figure 4.12: Coverage map of deploying 12 sensors using the context-aware method

According to Figure 4.11, 63.46 percent of coverage over the study area is reached at the end of optimization process compared to 59% at the starting point. Here, one may raise this question: that is it really a significant coverage improvement compared to the initial coverage before performing the optimization? To answer this question and also evaluate the efficiency of the local context-aware algorithm, a comparison between the results obtained from this method and a well-known global approach called CMA-ES (Akbarzadeh et al. 2013) has been conducted. Since there are many CI available that might be considered in context-aware method, the same conditions were applied to run both algorithms. In current implementation, just obstacles and surface elevation model are considered as the CI. The comparison was made using 8 sensors with random initial positions. In order to avoid the impact of initial positions over the final results (Argany et al. 2012), 32 runs for each method with 32 different initial random positions was performed. Table 4.1 presents the results of this comparison. The average values of coverage for both methods are two close values, which support the validity of obtained results from the proposed algorithm compared to a well-known optimization approach.

Table 4.1: Results of Context-Aware and CMA-ES optimization algorithms

Method	Avg. Coverage (%)	Best Coverage (%)
Context-Aware	51.17	52.83
CMA-ES	49.09	51.33

4.7.2 Optimization Considering the Restricted Area as CI

Thematic information is the next category of CI used in deployment optimization. Many parameters exist in the real environment to be considered in the knowledgebase as thematic CI. For example, several locations may be legally forbidden for the deployment of sensors, like private buildings, hospitals, military zones, highways, etc. There are other locations, which are difficult to access, or inaccessible for sensors to be installed, like aqueous zones, lakes, rivers, green spaces, and rough terrains. Considering restricted areas in the knowledgebase, sensor action is changed, and the reasoning engine in the optimization algorithm extracts new rules in form of defining new moves. In this case, sensors still move toward the farthest Voronoi vertex, but stop at position s_i' on $\overline{L_i}$, which $\overline{L_i}$ are the positions on $\overline{s_i v_{farthest}}$ that restricted areas R excluded from possible sensor positions. So, compared to the previous case study, here, the direction and orientation of a move are the same, but the stopping position might be different. Considering elevation as previous CI, the optimization algorithm returns the stopping position as the highest elevation on $\overline{L_i}$ using both pixel values from the map of elevation (DSM) and map of restricted areas.

$$\overline{L_i} = \{p \in \overline{s_i v_{farthest}} \mid p \notin R\}$$

$$s_i' = \underset{p \in \overline{L_i}}{\operatorname{argmax}} [elev(p)]$$

where *elev* is a function that returns the elevation of position p on the line $\overline{L_i}$.

Suppose that there is a building that has barred the connecting line between s_1 and v_4 on the line $\overline{AB}$ (Figure 4.13). Then the stop position of the move will be a position on $\overline{s_1 A}$ or $\overline{Bv_4}$, depending on weight values represent other types of CI such as elevation, or parameters explained afterward in next subsections.

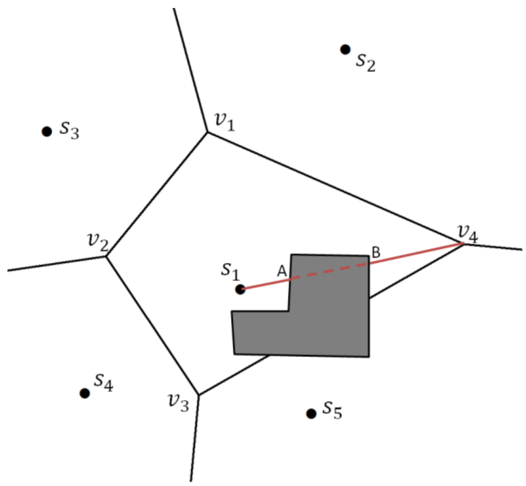

Figure 4.13: Sensor's move representation in case of considering the restricted area. Searching locations have been limited to lines S_1A, and Bv_4.

To evaluate integrating restricted area, two buildings and a street have been assumed as prohibited locations for installing the sensors (red zones in Figure 4.14).

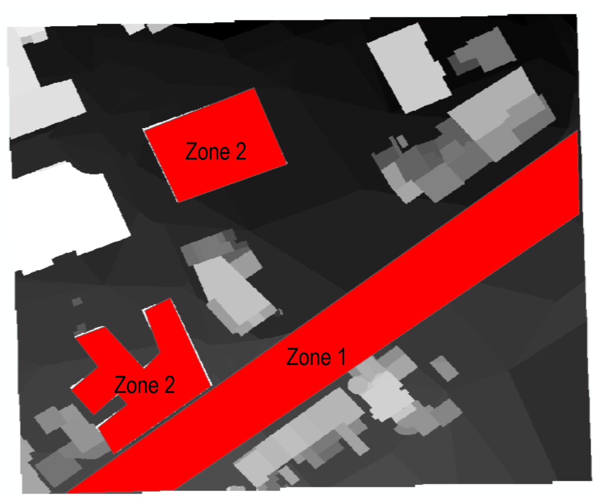

Figure 4.14: Illegal zones of sensor deployment: the street (Zone 1) and the buildings (Zone 2).

Firstly, the street (Zone 1) was considered as a CI constraint, and the optimization algorithm was run to deploy 12 sensors, which had been initially deployed on a triangular lattice grid, and overall coverage value of 56.19 percent was obtained. Final positions of the sensors and the covered region have been represented at Figure 4.15. As expected, there are no sensors located on the restricted street.

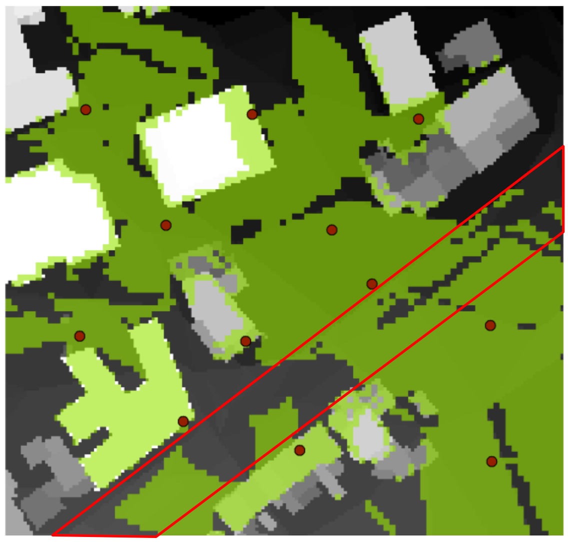

Figure 4.15: Coverage map of 12 sensors using the local context-aware method, considering the street (Zone 1) as the restricted area (the red border zone).

In the second phase of this implementation step, two buildings (Zone 2) have been added as the restricted areas and the street in the former step was considered as an authorized region. Similar to previous tests, the optimization algorithm was run over 12 sensors with the triangular lattice initial positions, and 59.48 percent of coverage was obtained. The results are represented in Figure 4.16. There are no sensors on the restricted buildings, despite the higher elevation on those regions. Compared to the previous case better coverage results are returned, when the street has been introduced as a legal place to install the sensors. Hence, the street might be taken into account more critical compared to the buildings in terms of installing the sensors for improving the coverage. This conclusion would be clear, because the area of buildings is less than the area of street in this study region. In fact, in this case putting sensors at the top of those buildings covers just the roofs since the sensing range is a short 35 meters range.

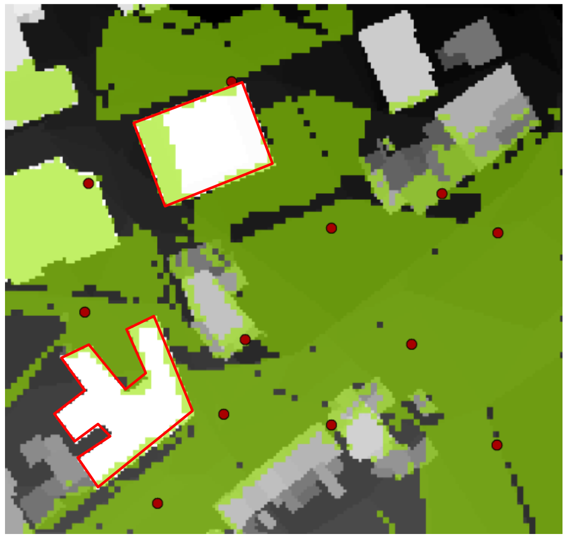

Figure 4.16: Coverage map of deploying 12 sensors using the context-aware method, considering the buildings (Zone 2) as the restricted area (the red border zones).

Finally, two buildings and the street (Zones 1 and 2) were entered to the algorithm as the CI of unauthorized areas. Initial parameters to run the algorithm are the same as earlier experiments. The coverage value is 55.52 percent. The outcome is presented in Figure 4.17. Adding CI as the weighted maps, expresses the ability of context-aware algorithm to accept different CI separately or together in different case studies according to the application requirements.

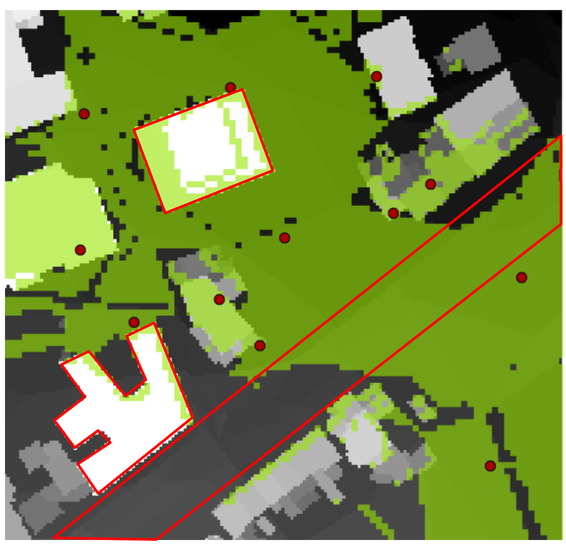

Figure 4.17: Coverage map of deploying 12 sensors using the context-aware method, considering the street (Zone 1), and buildings (Zone 2) as the restricted area (the red border zones).

In the following, we study to find the impact of increasing the number of sensors over the coverage value of the network, considering both Zone 1 and 2 as the restricted areas. It was started from 12 sensors and increased the number of sensors up to 35 sensors. The initial positions in all cases have been placed on the triangular lattice configuration. Table 2 shows the results of the implementations. In order to calculate the maximum possible coverage over the study area, the maximum coverage should be specified. Considering the area of the restricted buildings, the remaining region is 92.53 percent of the entire study area. Since sensors may move close to the street during the optimization process and make it covered, its area was not in calculation of the percentage of the maximum feasible covered region. Compared to the street, buildings do not have this characteristic due to their height. Hence, moving sensors close to buildings does not make them covered. Based on results presented in Table 4.2, almost all regions of the study area have been covered using 35 sensors. Figure 4.18 depicts the improvement of coverage by increasing the number of sensors over the study area. Figure 4.19 shows the configuration of the deployed sensors in the network and the covered area. Many buildings exist at top-right and bottom region of study area, which cause presenting high density of sensors. This may be also interpreted according to the restricted areas, in which sensors cannot be deployed, and push forward to cover the regions more complex.

Table 4.2: Impact of increasing the number of sensors on the coverage using context-aware method in case of considering the restricted area (Zone 1 and 2)

Num. of Sensors	12	16	20	24	28	35
Coverage (%)	55.52	58.15	59.51	66.14	73.08	87.56
Num. of Iteration.	11	8	9	19	15	34

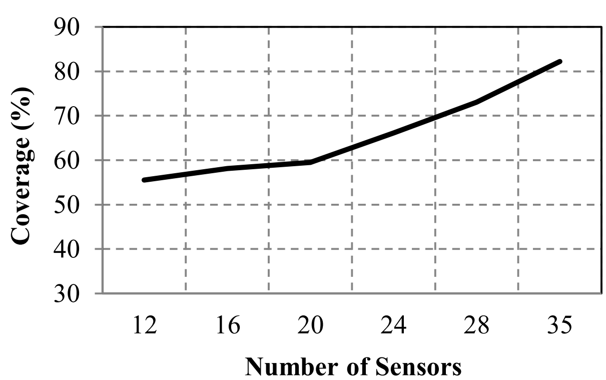

Figure 4.18: Impact of number of sensors on the coverage obtained by the context-aware method in case of considering the restricted area (Zones 1 and 2).

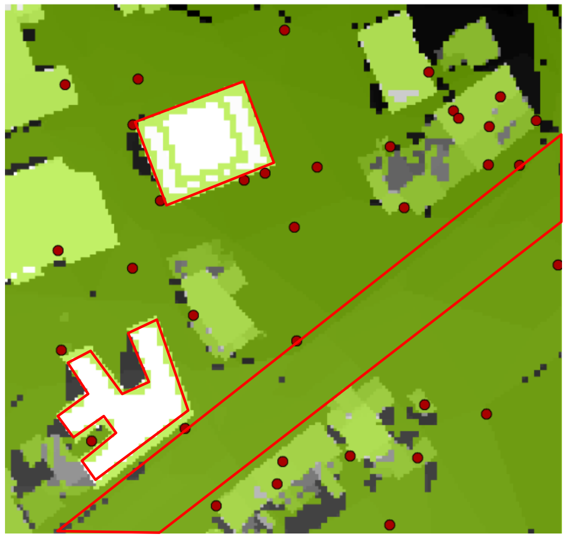

Figure 4.19: Coverage map of deploying 35 sensors using the context-aware method, considering the street (Zone1), and buildings (Zone2) as the restricted area (the red border zones).

4.7.3 Optimization Considering Desirability of Coverage in a Given Area as CI

Desirability of coverage is another type of thematic information that can be considered in the knowledgebase for the optimization process. Suppose that there are some places in the study area, where sensors cannot be set up, but there is a high interest in covering those regions. Then, the weighted map for this CI is defined as follows. Given an environment Ξ, let C_i be the circular sensing region with the radius r of sensor s_i centered at the position p_i, then:

$$C_i = \{p \in \Xi \mid \|p - p_i\| \leq r\}.$$

Suppose that positions are corresponding to pixels, then to define the places with higher concern of coverage the w_{dc} is defined as the weight of desirability of the coverage in the environment Ξ. Evidently, the places with higher desirability of coverage should get higher weight (w_{dc}) compared to the rest of the study area, e.g., the street in Figure 4.20. To consider this weight in the sensor move, each possible new sensor position p_i gets a score, which is the sum of weights within C_i.

$$score_{dc}(p_i) = \sum_{p_j \in C_i} w_{dc}(p_j)$$

The new rule extracted by the reasoning engine is to move sensors toward the desired region to cover it as much as possible, while sensors should not enter the zone. As in previous experiments, each sensor moves on $\overline{s_i v_{farthest}}$, but to respect the new rule, it stops at the position s_i' with the maximum $score_{dc}$. In this case, the constraint presented in 6.2 needs to be already checked, and as a result the stop position should be out of the restricted area as well.

$$s_i' = \underset{p_i \in \overline{L_i}}{\operatorname{argmax}}\,(score_{dc}(p_i))$$

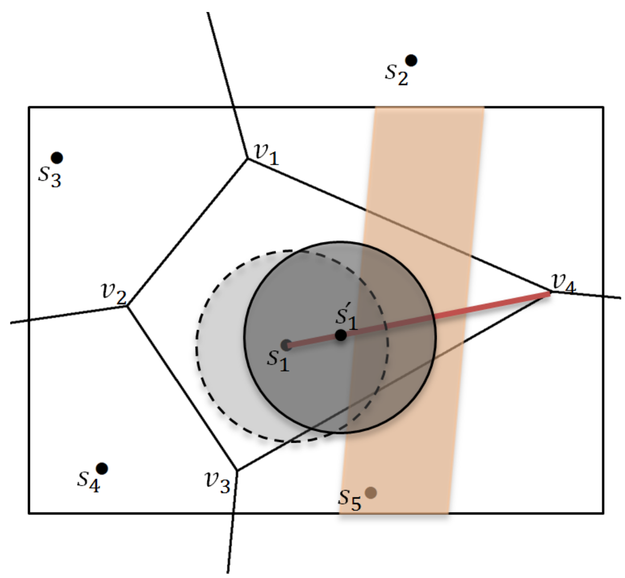

Figure 4.20: Sensor's move representation in case of considering circular coverage and desirability coverage at the pink area (street), s_1 represents the initial sensor position, s_1' represents the position with highest weight score on the line $s_1 v_4$.

Figure 4.21 shows how a simulated weight map has been created to consider the CI of desirability of coverage. It represents how the $score_{dc}$ is calculated followed by the movement of a sensor in green cell toward a position with higher score (orange zone).

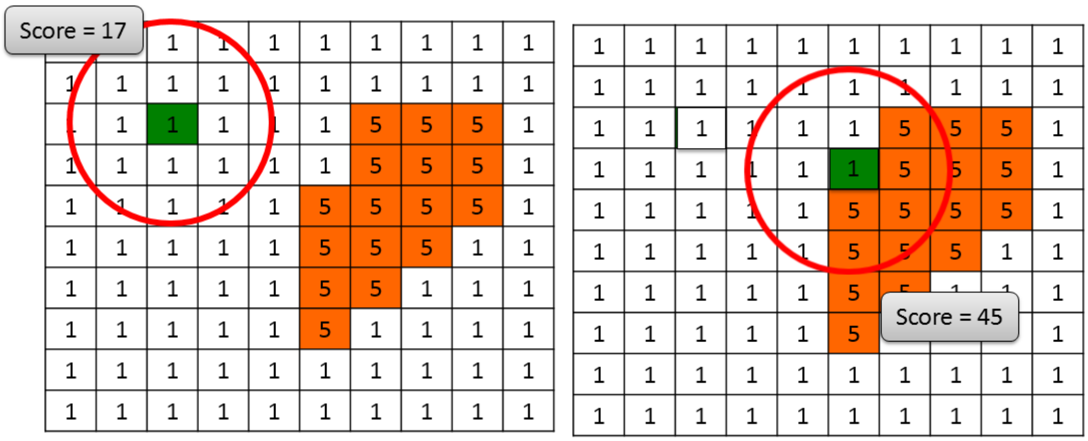

Figure 4.21: Simulation of the $score_{dc}$ on the weight map, followed by finding new sensor position regarding CI of desirability of coverage.

To evaluate the performance of the method when the desirability of coverage has been considered in a specific area, the optimization algorithm was run over 12 sensors with triangular lattice initial position. Zone 1 was introduced as the area with high interest to be covered, while it is unauthorized for sensors to be installed. Figure 4.22 represents the final sensor positions and the covered area. Compared to case of deploying 12 sensors without introducing any restricted area (Figure 4.12), and deploying 12 sensors considering Zone 1 as the unauthorized region, results show how 6 sensors among all, which were closer to Zone 1, have moved and stopped beside the street to make it covered (Blue dots on Figure 4.22). Overall coverage of 58.48 percent has been obtained. In this case, the street area has been almost covered. Having covered the desired region with 12 sensors, the question may arise whether the desired region could be covered using fewer sensors deployed in the study area. It means the desired region will be covered applying less optimization process. To evaluate this assumption, the algorithm was run over 8 sensors with the triangular lattice initial position. Figure 4.23 presents the final sensor positions and the covered area. Overall coverage of 49.57 percent has been obtained. The orientation of the sensors in Figure 4.23 shows that they were deployed with the purpose of covering the street (red border) as well as maximizing the overall coverage. The blue dots sensors have been moved to cover the desired area, while other sensors have been configured to cover the rest of study area. For example, a sensor at the right side of the street has come closer to the street during the optimization, but not too close like other sensors at the left side, because it belongs to an area with fewer obstacles on the terrain. Thus, if it comes closer to the street to cover an area, which has been already covered by another sensor, the coverage may be lost on previously covered area. Consequently, as explained before, the reasoning engine extracted movement rules to respect both purpose of covering the desired area as well as overall coverage over the network.

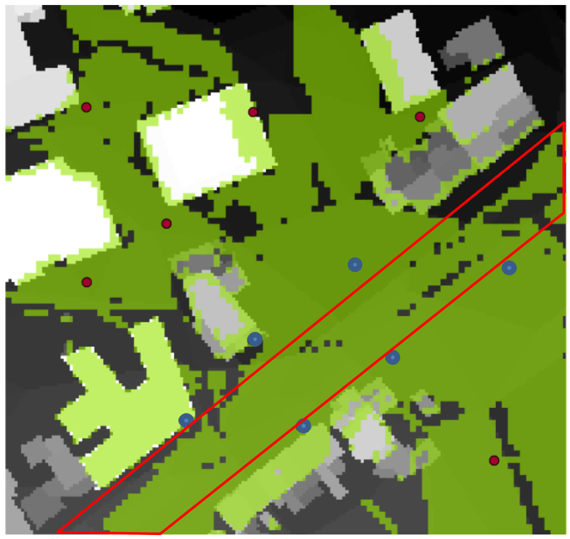

Figure 4.22: Coverage map of deploying 12 sensors using the context-aware method, considering the street (Zone 1) as the desired region to be covered (the red border).

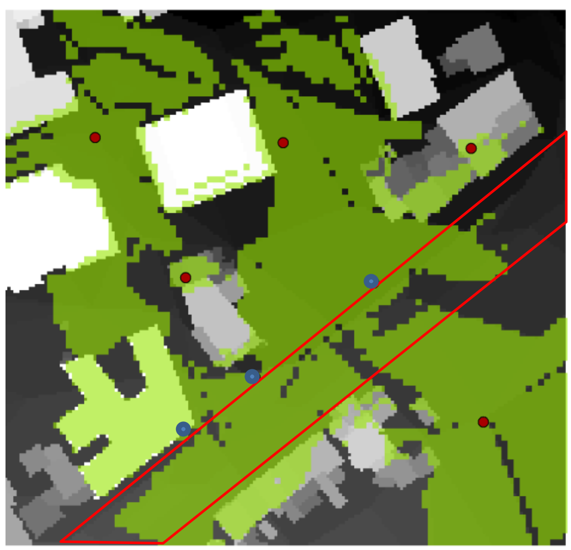

Figure 4.23: Coverage map of deploying 8 sensors using the context-aware method, considering the street (Zone 1) as the desired region to be covered (the red border).

4.7.4 Optimization Considering the Environment Activities as CI

Sensor placement in an environment with a critical asset is the next thematic CI that is added to the knowledgebase of the context-aware algorithm. Assume a critical asset to be monitored for preventing any undesired access with a slight activity in its environment Ξ, which is located beside a street with a high level of activities. Thus, the sensor movement rules need to be modified regarding to the interest of monitoring any intrusions within the fenced area, while sensor should not be always activated due to the traffic or other activity on the street. In this case, two types of weight maps are defined: 1) $w_{activity}$, which is the weight corresponding to the degree of activities in the environment, and 2) w_{dc}, that is the desirability of coverage weight with respect to the area that should be monitored. Obviously, the area with high amount of activities takes higher $w_{activity}$, and the desirable area supposed to be covered gets a higher w_{dc}. Let C_i be the circular coverage region of sensor s_i centered at the position p_i, then the score value of all possible positions p_i is:

$$score_{actdc}(p_i) = \left(\sum_{p_j \in C_i} w_{dc}(p_j) \right) - \left(\sum_{p_j \in C_i} w_{activity}(p_j) \right)$$

Similar to the Section 4.7.3, the direction of sensor move is toward the farthest Voronoi vertex, and the stop point is at the position with the maximum $score_{actdc}$ (new movement rule).

$$s_i' = \underset{p_i \in \overline{L_i}}{\operatorname{argmax}} \, (score_{actdc}(p_i))$$

The reasoning engine also checks all previous CI, such as object elevations (used to define obstacles and visibility) and restricted areas, which were provided in form of different weighted maps, in addition to the new situation. It means for each pixel, there are different values related to previous extracted CI, plus the new value (score) related to the environment activity.

To evaluate this case study, Zone 3 was defined as a region with high desirability of coverage including low activity, which is located beside Zone 1, which is a street, containing high activity and low interest of being covered (Figure 4.24). Both Zone 1 and Zone 3 are unauthorized zones for installing sensors. Same as previous case, the algorithm was run over 12 sensors with similar initial conditions. Figure 4.24 has the final sensor positions and the covered regions. Compared to the case of considering the street as the desirable area to be covered (Figure 4.22), which 6 sensors were moved to cover the street, in this case 3 sensors were configured by the local context-aware optimization algorithm on the proper locations to cover Zone 3 (blue dots on Figure 4.24). Accordingly, the coverage over the street may be decreased while all surface of Zone 3 is covered. In this case study, the overall coverage is 55.72 percent, which is lower that other cases. It shows the importance of sensor configuration to cover a special place on the study area and avoid deploying sensors in an area with high activity, but low interest of being covered.

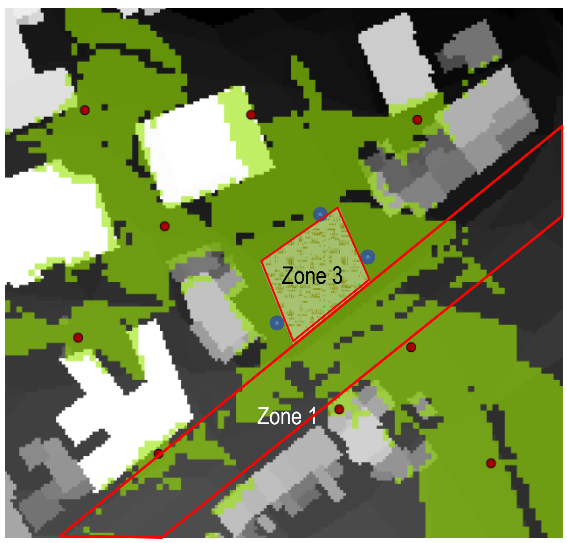

Figure 4.24: Coverage map of deploying 12 sensors using the context-aware method, considering the activity in the network; Zone 3: the area with low activity, but high interested to be covered

4.8 Discussions and Conclusions

A local context-aware optimization method for sensor network deployment has been proposed in this paper, which considers the local information from the environment and the relevant information on the network. The main objective of the paper was to propose a more realistic context-aware deployment algorithm for sensor networks in a given environment. As mentioned in Sections 4.2 and 4.3, integrating local information and relations of the network and surrounding environment helps to conduct an efficient sensor network deployment. Some instances of such information include adjacency relations, sensors configurations, obstacles that are blocking the line-of-sight, and the information about the physical environment elements. Accordingly, the concept of context was investigated and expanded for sensor network deployment. The CI then was categorized to three categories of spatial, temporal, and thematic to be clearly involved in sensor deployment. The mentioned investigations led authors to propose a flexible conceptual framework to handle sensor placement using Voronoi diagram and contextual information. Based on the proposed conceptual framework, a novel local context-aware optimization algorithm was developed. The proposed algorithm does not depend on the oversimplification of assumptions as is usually observed in other existing optimization algorithms. The novelty of our algorithm lies in explicit consideration of the local CI, such as environmental information, spatial locations, sensor adjacencies in the network, thematic and legal information for sensor placement, and sensors temporal configuration. Despite the capacity of proposed algorithm to consider complex CI, it is simple and easy to implement. In addition, it used a flexible methodology that can accommodate all relevant information that would influence sensor placement. Thus, the proposed approach can address different sensor configuration under different circumstances or different environmental CI and sensor parameters. Consequently, if there are any changes in sensor parameters or environment, the optimization algorithm can simply take in the new relevant CI and regenerate a new sensor placement design adapted to the new situation.

In order to validate the proposed algorithm we have conducted several experiments. First, the results of the local context-aware algorithm were compared with a well-known global optimization algorithm (CMA-ES) in one case. The comparison shows almost the same percentage of final coverage value over the study area for both methods, while the number of iterations in the proposed local approach is significantly less than the global method. The local context-aware approach uses the local CI and spatial relations to perform the optimization. It explicitly considers the physical reality of the environment, instead of using the probabilistic information, which is generally used in global non-context-aware methods.

The developed algorithm was evaluated over many relevant case studies for performance with different application needs. In order to avoid the impact of different initial positions on the final outputs, the same initial conditions were applied at the starting point of optimization. Elevation and viewshed information were the first level of CI used in the local approach. For the next case study, some restricted areas were introduced to the algorithm. Giving this CI, the optimization algorithm analyzed sensor displacement in the network, and appropriate actions were determined. Another investigation was made to find how many sensors would be enough to cover the whole study area. It was conducted by increasing the number of sensors and its impact over the coverage improvement. To analyze the capacity of context-aware method in more complex situations, the desirability of coverage was added as supplementary CI. Environmental activities such as monitoring an environment with a slight activity containing a critical asset for preventing any undesired access located beside a street with high level of activities were considered as the last part of the investigation over various CI case studies. In that step, regions with high activity and low desire of coverage were introduced to the algorithm. The extended algorithm was adapted to cover the desired region without being affected by the attraction of high activities of the surrounding regions. These inquiries illustrate how the proposed local context-aware algorithm is efficient to perform a sensor deployment optimization considering environmental and network CI.

The presented approach is a context aware automated sensor deployment optimization method based on environmental and network information. An specialized context-aware process was introduced to exploit complex environmental information. The algorithm maximizes the performance whereas the processing time is minimized based on an optimal number of sensors displacements in the network. In addition, the proposed method profited from a local refinement of deployment using a deterministic solution, which avoids applying the stochastic black box methods.

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CHAPTER 5

Impact of the Quality of Spatial 3D City Models on Sensor Networks Placement Optimization

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Keywords: *sensor network deployment; coverage problem; optimization; spatial data quality; 3D city model*

5.1 Abstract

Sensor networks are increasingly used for tracking, monitoring and observing spatial dynamic phenomena in the real world (e.g. urban area). In order to ensure an efficient deployment of a sensor network, several optimization algorithms have been proposed in recent years. Most of these algorithms rely on oversimplified sensor models. In addition, they do not consider information on the terrain topography, city models, and the presence of diverse obstacles in the sensing area (e.g. buildings, trees, poles). Only some of those optimization algorithms attempt to consider the terrain information in the optimization of a sensor network deployment. However, most of these algorithms consider that the spatial models used for this purpose are perfect representations of the reality and are not sensitive to the quality of the information. However, spatial models are simplified representations of a complex reality, and hence are inherently uncertain. In this paper we investigate the impact of the spatial data quality on the optimization of a sensor network and its spatial

coverage in an urban area. For this purpose, we investigate specific implications of spatial data quality criteria for a 3D city model that will be used in sensor network optimization algorithms. Then, we analyze the impact of some of those criteria on the estimation of sensor network coverage. Afterwards, a case study for sensor network deployment in an urban area is presented. This case study demonstrates the impact of 3D city models quality on the estimation of coverage using global and local optimization algorithms. Finally, the results obtained from this experimentation are presented and discussed.

5.2 Introduction

Sensor networks are increasingly used for tracking, monitoring and observing spatial dynamic phenomena of the real world (Nittel 2009). The benefit of using such networks is to access remote or harsh areas and observe phenomena in these locations at the lowest cost possible. The cost of a sensor network deployment depends mainly on the number of sensors used and how these sensors are placed in the environment to be monitored. Hence, in order to maximize the spatial coverage of such networks, optimization algorithms can be used to find the best position for each sensor in the network. However, most of the proposed placement algorithms do not consider the nature of real environments (Aziz et al. 2009; Bharathidasan & Ponduru 2004; Nittel 2009). In addition, the few works that take into account the environmental information in their methods (Wang & Tseng 2008; Akbarzadeh et al. 2001) do not study the impact of the inherent uncertainty of spatial data in the estimation of sensor network coverage.

There are many objects and obstacles in the environment that may constrain the spatial coverage of a sensor network. Therefore, it is necessary to consider these elements in sensor network optimization algorithms. For example, in an urban area, the presence of buildings, roads, streets, trees, and poles should be considered in sensor deployment. In a natural area, the topography of the terrain and other properties of the environment such as vegetation must be known. Spatial models are very rich sources of geospatial information that can be used inside the optimization algorithms. However, spatial models are simplified representations of a complex reality, and hence are inherently uncertain. The uncertainty in spatial data may be related to the methods used for the acquisition, processing, or manipulation of spatial data, and it may significantly affect the spatial coverage of a sensor network.

Some of the most important types of datasets, which are used as spatial models in sensor network deployment, are Digital Terrain Models (DTM) and Digital Surface Models (DSM). The quality of these models is varied and depends on the accuracy of the initial datasets, which are used to produce them as well as the instruments, which have been used to collect those datasets. For example, both digital terrain models and digital surface models may have some inaccuracies, which involve some unintentional errors in final results. Since we have errors and inaccuracies within the initial datasets, it is inevitable that these errors will be propagated when these datasets are used for deployment of sensor networks. So, accuracy of sensor placement strongly depends on the quality of spatial models that are used in optimization algorithms. Also, the communication between sensors in a given network may be affected by the quality of the data as well. In fact, the position of sensors and their communication range are important to ensure reliable communication between sensors.

In this paper, we investigate the data quality elements with an emphasis on those that are the most relevant for 3D city models. We study the impact of those elements on sensor network coverage estimation. Then, we investigate the impact of the 3D dataset's quality, which will be introduced as initial input in the sensor network deployment optimization algorithms on the final results. Our goal is to determine how sensitive different optimization algorithms are to the quality of input datasets and what their behavior will be.

The remainder of this paper is organized as follows. Section 5.3 presents a literature review describing various models and solutions of the sensor deployment optimization based on 3D city models. Local and global approaches for sensor deployment optimization are discussed in this section. In Section 5.4, the quality elements for 3D city models are introduced. First, standard spatial data quality elements are presented and then the most relevant data quality elements for 3D city models are further investigated and their implications for sensor placement are discussed. Section 5.5 presents an analysis of the quality impact of 3D city models on the sensor network deployment. The issue of how 3D model quality affects the results of optimization methods will be discussed. Section 5.6 contains the experimentations and results. Several maps with different quality levels have been prepared and tested with three optimization algorithms. The sensitivity of the optimization methods to the quality of input data is investigated in that section. Finally, Section 5.7 concludes the paper with discussion of the results and proposal of new avenues for future work.

5.3 Sensor Network Deployment Optimization Based on 3D City Models

Efficient sensor network deployment is an important issue in the sensor network field, as it affects the coverage and communication between sensors in the network. Nodes use their sensing modules to detect events occurring in the region of interest (e.g. urban area). Each sensor is assumed to have a sensing range, which may be constrained by the phenomenon being sensed as well as the environmental conditions. Hence, obstacles and environmental conditions affect network coverage and may result in holes in the sensing area. The definition of coverage differs from one application to another (Aziz et al. 2009; Ahmed et al. 2005; Ghosh & Das 2008; Huang & Tseng 2005; Megerian et al. 2005; Meguerdichian et al. 2001). In this study, the definition of coverage is based on a direct visibility between a sensor and a target point (e.g., camera for traffic monitoring) (Figure 5.1). The coverage of a point in a sensor network means that this point is located in the sensing range of at least one sensor node. The coverage area of each node is usually assumed to be uniform in all directions. In this case, the sensing range is represented by a disk around the sensor. Failing this condition for some points in the region of interest results in coverage holes (Ahmed et al. 2005).

Figure 5.1: Direct visibility between an observer and a target, point A is visible while point C is invisible because its line-of-sight is concealed at point B.

Hence, one important issue in sensor network deployment is finding the best sensor position to cover the region of interest. Regarding the mentioned definition of coverage in sensor network, the coverage problem basically means placing a minimum number of nodes in an environment, such that every point in the sensing field is optimally covered (Aziz et al. 2009; Ghosh & Das 2008). Nodes can either be placed manually at predetermined locations or dropped randomly in the environment and then repositioned to optimal locations. It is difficult to find a random scattering solution that satisfies all the coverage and communication conditions between sensors.

There are several approaches in the literature to solve the problem of sensor network coverage (Niewiadomska-Szynkiewicz & Marks 2009; Romoozi & Ebrahimpour-komleh 2010; Ghosh & Das 2008). In general, these approaches are classified into global and local optimization approaches. Global optimization approaches are used to find the global optima of a function (coverage function) or a set of functions for the whole study area. Conversely, local optimization methods are used to find local optima among a number of candidate solutions. Candidate solutions here could be the sensors positions or final coverage, which is supposed to be optimized according to the coverage function. Local methods start with an initial value in the space of candidate solutions and then iteratively move to neighbor values or solutions by applying local changes until the optimal solution is found or a time bound is achieved.

5.3.1 Global optimization approaches

Simulated Annealing (SA) and Covariance Matrix Adaption Evolutionary Strategy (CMA-ES) are two examples of global optimization methods used for sensor network deployment (Akbarzadeh et al. 2010; Akbarzadeh et al. 2001). These methods will be used in Section 5.6 to compare the impact of data quality on sensor network deployment given their performance and popularity in global optimizations (Akbarzadeh et al. 2001).

Simulated Annealing (Kirkpatrick et al. 1983) is a classical metaheuristic optimization algorithm, which is inspired by the annealing process of material in metallurgy. In fact, temperature is the controlling mechanism used to convert material from a high-energy state into a low-energy solid condition. This process is imitated in SA, where the temperature controls the number and spread of accessible solutions from a given solution in the search space. SA starts with random sensor positions in the 3D study area with a high initial temperature to allow a random walk in the search space. As the temperature is gradually decreasing the system becomes greedier, only to allow moves in the search space which improve the performance of the solution to find optimized positions which best served coverage. The process is completed with a temperature close to zero. To calculate the coverage, a coverage function, which will be introduced in Section 5.3.3, is supposed to be optimized by means of an optimization algorithm.

CMA-ES is part of the evolutionary algorithm family. It is a black-box stochastic optimization method, in which new candidate solutions (sensors positions) are sampled according to a multivariate Gaussian distribution, which is adapted in the course of the optimization (Hansen & Ostermeier 2001). For sensor network deployment optimization, the initial position and orientation of sensors in a 3D model can be considered as a candidate solution. So, any variations or inaccuracies in the 3D model affect the position and orientation of the sensors and hence, directly impact the formation of the next solutions. The sensor positions will be evolved through the optimization and finally, the solution with the best coverage is selected as the final result (Akbarzadeh et al. 2013).

5.3.2 Local optimization approaches

The second category of optimization algorithms for sensor network deployment is the local approaches. Some geometric solutions found in the literature take into account the spatial relations between the elements of 3D model (search space). When there is not enough information available about the environment, sensors are deployed randomly at the first placement, and then some deployment strategies take advantage of mobility and try to relocate sensors from their initial position to optimize the network coverage. In these cases, spatial information, sensor's positions and movement strategies are provided based on 3D models. VECtor-based and VORonoi-based algorithms are two mobility-based methods that use the Voronoi diagram in their approaches (Argany et al. 2011). The spatial coverage of sensor networks in 3D models is much related to the spatial distribution of the sensors. In other words, the geometric solutions try to distribute the sensors in the environment by using 3D models so that as much coverage as possible will be obtained. These approaches can be used to detect coverage holes in 3D datasets as well as healing those holes.

The VORonoi-based algorithm (VOR) is a pulling strategy; this means that sensors cover their local maximum holes. This method has been selected to study the impact of data quality in Section 5.6 because of its geometrical performance and ability to model the environment (Argany et al. 2011). In this algorithm, each sensor moves toward its farthest Voronoi vertex until this vertex is covered. The disadvantage of the VOR algorithm is that each sensor may be selected to move but there is no criterion to define where it should stop moving. A 3D model of the environment can help us to define this threshold, which means that sensors stop moving when they arrive at the point with a higher elevation than their initial position. The line of movement corresponds to the line between the initial sensor location and farthest Voronoi vertex. In the rest of the paper we call this approach the enhanced VOR algorithm. Here, Voronoi cells define the regions in the study area which should be covered by the sensor inside the cell. Since the sensing range of sensors is limited, then some holes may exist beyond the sensing area of the sensors (Figure 5.2).

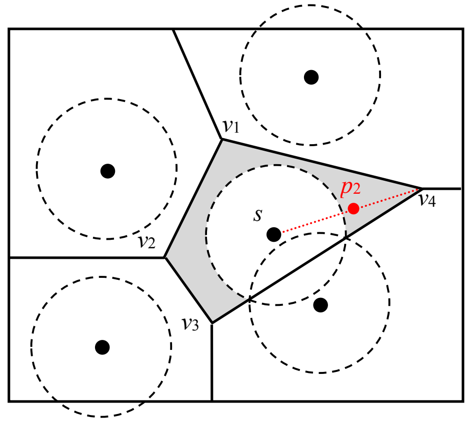


Figure 5.2: Movement of a sensor in the VOR algorithm.

5.3.3 Coverage estimation using 3D city models

In this paper, coverage is defined based on the concept of line-of-sight. Line-of-sight can be defined as the direct visibility between an observer and a target point. Given the sensor position p_i, if there is no obstacle between p_i and the target point q, then the latter is visible. Also, if q is in the sensing range of s_i, coverage is achieved (Figure 5.1). Viewshed is another term, which is used in optimization algorithms. It is defined as an area in the maps that is visible from a specific sensor position. Viewshed algorithms use elevation of each cell in a DTM to determine visibility to or from a particular cell (sensor positions). The visibility depends on the following notions: observation points, horizontal and elevation coordinates (x_i, y_i, z_i), vertical offsets (the vertical distance to be added to the z coordinate value of a location on the surface), horizontal and vertical sensor orientation (ξ_i, θ_i), and the sensing distance (Figure 5.3). Line-of-sight, viewshed, visibility, and position of obstacles are essential information, which can be directly obtained from 3D models provided by a geographic information system.

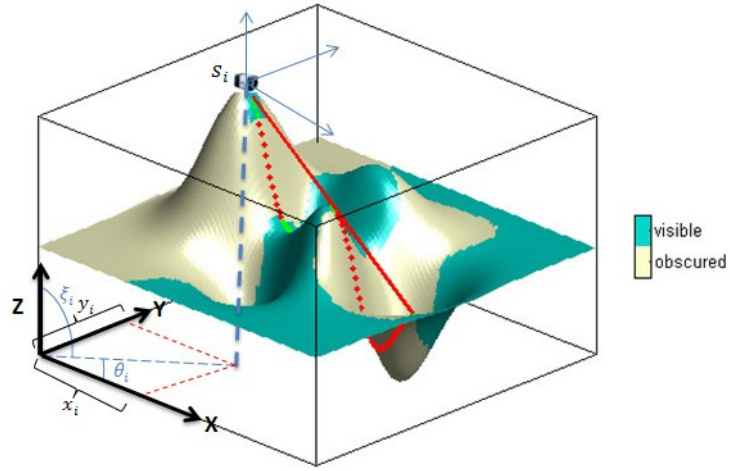


Figure 5.3: Parameters and visibility of sensor s_i in a 3D model

To find the optima in the category of global optimization methods, it is necessary to define a coverage function. This function is expressed based on the properties of the sensors and the environment information. The sensing model in our investigation is related to distance between sensor and target locations, sensor orientation, and visibility. If we assume that $p_i = (x_i, y_i, z_i)$ is a sensor position, θ is pan angle around its vertical axis and ξ is the tilt angle around the horizontal axes then, the coverage function $C(s_i, q)$ for sensor s_i at point *q* can be defined as a function of distance $d(s_i, q) = \|p_i - q\|$, pan angle $p(s_i, q) = \angle_p(q - p_i) - \theta_i$, tilt angle $t(s_i, q) = \angle_t(q - p_i) - \xi_i$, and visibility $v(s_i, q)$ from the sensor (Akbarzadeh et al. 2001):

$$C(s_i, q) = f\left[\mu_d(\|p_i - q\|), \mu_p\left(\angle_p(q - p_i) - \theta_i\right), \mu_t(\angle_t(q - p_i) - \xi_i), v(p_i, q)\right] \quad (1)$$

Where $\angle_p(q - p_i) = \arctan\left(\frac{y_q - y_{p_i}}{x_q - x_{p_i}}\right)$ is the angle between the sensor s_i and the point *q* in the horizontal plane and $\angle_t(q - p_i) = \arctan\left(\frac{z_q - z_{p_i}}{\|p_i - q\|}\right)$ is the angle between the sensor s_i and the point *q* in the vertical plane. Parameters $\mu_d, \mu_p, \mu_t \in [0,1]$ represent membership functions that need to be defined according to the coverage conditions.

In order to cover point q by sensor s_i, we should consider the sensing range, sensing angle and visibility. These three parameters can be extracted directly from the 3D model, which will be used to make the optimization. The parameters $d(s_i, q)$ and sensing range are calculated based on the (*x, y, z*) coordinates of the sensor and target location points which are provided by the 3D model. Pan $p(s_i, q)$ and tilt $t(s_i, q)$ angles are characteristics which are related to the orientation of the sensor as well as the distance to point q which is calculated from the 3D model.

As described in section 5.3.2, the enhanced VOR algorithm is a local optimization method, which attempts to move sensors and "heal" uncovered areas. In each step of iteration, visibility, and then viewshed are calculated based on the line-of-sight between the sensors and targets. The covered area for each sensor corresponds to the intersection of its sensing range and the viewshed area. As mentioned before, visibility and viewshed are obtained from 3D models of the study area. Hence, coverage is affected by the quality of the 3D models.

5.4 Spatial Data Quality in 3D City Models

The deployment of a sensor network in an urban area requires the use of 3D city models. A 3D city model may contain building models, water bodies, transportation objects, vegetation, and city furniture. The building model is the most detailed and frequently used thematic concept of a city model. Different types of buildings may exist in city models, e.g. residential, public, and industry with different details, height, shapes, and volumes. Usually, transportation objects are represented as a linear network in 2D models, but they are geometrically described by 3D surfaces in 3D urban models. In 3D models, roads can be depicted by a traffic area accompanying the auxiliary objects and obstacles, which bar or affect the traffic transportation. Vegetation features are important components in 3D models, which help us to recognize the surrounding environment. They can be represented as single vegetation objects or plant cover (multi solid) objects in 3D city models. City furniture are potentially movable objects such as traffic lights, signs, flower buckets, benches, and bus stops which can be found in residential, traffic, and public areas. Spatial location recognition to install sensors can be improved by taking into account these city furniture details in the 3D city models.

The quality of spatial data in a 3D city model that may be used in sensor networks optimization algorithms can undermine its efficiency. According to the spatial data quality literature, spatial data quality depends on several factors; the "internal" quality of spatial data is determined by its actuality, geometric and semantic accuracy, genealogy, logical consistency, and the completeness of the data. This view reflects the producer's perception of quality, which differs from the notion of "external quality". External quality is focused on "fitness for use"; it is defined as the level of fitness between the data and the needs of users (Mostafavi et al. 2004; R. Devillers 2006).

There has been a consensus about the criteria of internal quality between the ISO, FGDC, and CEN to use the same criteria for geospatial data quality (R. Devillers 2006). ISO 19113 (Quality principles) and ISO 19114 (Quality evaluation procedures) are two pairs of standards which define the principles for describing geospatial data quality. The ISO 19113 recommends five grouping of data quality elements, which can contain quantitative information. These criteria are completeness, logical consistency, positional accuracy, temporal accuracy, and thematic accuracy (Kresse & Fadaie 2004). The ISO 19115 (Metadata) provides the procedures for quality evaluation by defining a dictionary for the data quality elements. According to ISO 19115, metadata contains both quantitative and non-quantitative information. The ISO 94 (Quality management and quality assurance - Vocabulary) addresses the external quality elements. Investigations on the criteria of external quality have been limited to just a few authors. Among them, Wang and Strong (1996) propose four groups for external quality dimensions: intrinsic data quality, contextual data quality, representation data quality, and accessibility data quality. Bédard and Valliére (1995) have investigated the external quality for geospatial data and mentioned these categories as the quality elements of a geospatial dataset: definition, coverage, lineage, precision, legitimacy, and accessibility. Oort (2006) has done a comprehensive study on data quality description and applications. He has defined essential terms of spatial data quality and introduced variable methods of investigating the accuracy and errors in spatial and land cover classification. The studies presented so far have mostly considered 2D models, although, they can be used for 3D models. Walter (2006) has conducted research on quality control of 3D geospatial data. He mentioned the spatial data quality elements that have a clear meaning in 3D models. He also proposed an automatic update method for the quality control of 3D models composed of laser data, aerial and terrestrial images. His approach is processed with an image interpretation algorithm in order to control for the existing objects and find new objects that are not in the database.

It is difficult to find an exact investigation of the elements of data quality in 3D models. So, in the following list we propose the most relevant criteria of data quality for 3D spatial models.

- *Positional Accuracy*: In general, accuracy addresses the probable differences between the measured and true values. It can be divided into relative and absolute accuracy. Positional accuracy is the accuracy of coordinate values and categorized as vertical and horizontal. In 3D city models, compared to 2D models, apart from X and Y coordinates, Z values should be considered in positional accuracy analysis. For example, the accuracy of the height of buildings and other 3D objects is important as well as horizontal positions and it has a direct impact on 3D issues such as shadow and visibility analysis.
- *Logical Consistency*: Logical consistency of a spatial database constitutes an important part of the determination of the internal spatial data quality. It may be defined as the degree of consistency of the data with respect to its specifications. It concerns the question of whether collected data are related to other data in a logical sense. In other words, it refers to the absence of apparent contradictions in a database (Walter 2006). For instance, in 3D datasets, logical consistency can refer to topological relations. For example, extracting building footprints and extruding them is one of the simplest methods to construct 3D city models from 2D data. So, if the topological relations between the footprints are not taken into account, the resulting 3D city model may not be topologically and hence logically consistent (Ledoux & Meijers 2009).
- *Lineage* concerns the question of how the data are collected and the method of how the data have been entered in a computer program. This information contains a short history of the data producer, data source, data capturing, and data processing methods. In 3D datasets, the lineage can refer to the historical information about data acquisition, data representation and data processing. The question of which kind of instrument or acquisition method has been used to collect the dataset will be

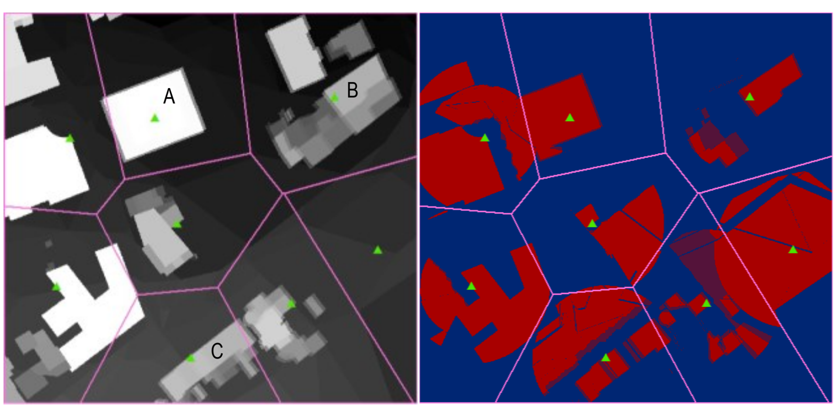
answered in the data acquisition part of the lineage information. In data representation we will find the method by which the dataset has been represented, e.g. regular grid, TIN, mesh, 3D faces. In terms of data processing, lineage may contain information about processing methods such as different kinds of interpolation (e.g. nearest neighbor, bilinear, and bicubic). This may also describe the methods used for 3D modeling process.

- *Semantic Accuracy* addresses the question of whether the data really express its intended meanings. This criterion provides information on the difference between the values of spatial attributes and their real values. In 3D models, we are again concerned with the semantics of spatial objects. More specifically we are concerned with the semantics of 3D objects. For example how to represent buildings regarding their definitions and shapes (factory, hospital, residential, educational, etc.). What are the spatial integrity constraints that exist between 3D objects and how accurately are they defined with respect to the reality?
- *Completeness* indicates the question of whether there is anything more to add to the data. This criterion is usually determined based on the matrix of omission (abnormal absence) and commission (abnormal presence) of some objects in a spatial model. This can also be related to the levels of detail (LOD) used to represent spatial information in 3D models. Omission or commission of some objects (e.g. trees and buildings) or the levels of detail in their representation (e.g. missing balconies in a 3D building model) in a 3D city model have an impact on the sensor positions obtained from the optimization algorithms. Also, it will have a significant impact on the estimation of its spatial coverage.
- *Temporal Accuracy* concerns the question of whether the data is up to date or not. For example are there some new constructions in a 3D city model, which should be added to the dataset, or it is necessary to delete some blocks from the dataset.

5.5 The Impact of 3D City Models Quality on Sensor Deployment

As mentioned in Section 5.3, the sensor placement optimization algorithms that are applied in our experimentation use line-of-sight and viewshed to calculate spatial coverage. These two concepts allow visible and invisible objects to be identified and hence, define covered and uncovered areas in the region of interest. The quality of 3D city models has a direct impact on the estimation of these values. In the following, we will present and discuss these impacts with respect to some of the quality criteria that we presented in the previous section.

Positional accuracy has a direct impact on the estimation of the visibility in a 3D city model. The positional accuracy may be presented as a small displacement in the position of the objects, which can be either horizontal or vertical or both. Even a few centimeters inaccuracy in horizontal or vertical positions of objects or sensors can block the line-of-sight between a sensor and a target. Fig.4 shows the impact of changing the positions of buildings on the obtained coverage. In Figure 5.4(a) positions of three buildings have been displaced and overlaid at the same DTM. So, buildings at points A, B, and C are opaque. Figure 5.4(b) depicts the change of coverage because of inaccuracy in the positions of those buildings. Figure 5.5 shows the impact of completeness on sensor network coverage. In Figure 5.5(a), three buildings have been removed from the dataset. Figure 5.5(b) depicts the impact of elimination on the final coverage. This situation may also occur in datasets due to temporal accuracy and the demolishing of some buildings. Conditions have been considered in an exaggerated manner in both Figure 5.4 and 5.5.



(a) (b)

Figure 5.4: Impact of positional accuracy on sensor network coverage: (a) small displacement of three buildings at positions A, B, and C shown on DTM (b) area which will be covered after the displacement shown in light red.

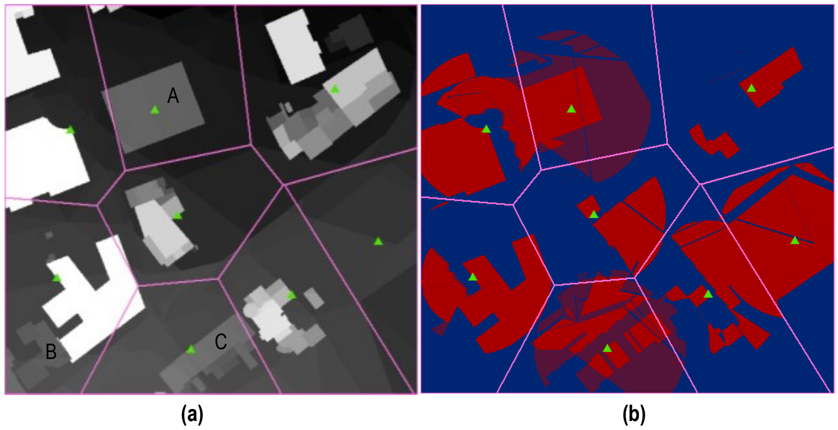


Figure 5.5: Impact of completeness on sensor network coverage: (a) elimination of some blocks at positions A, B, and C shown on DTM (b) area which will be covered after elimination shown in light red

In 3D city models, sensor nodes and 3D objects should be logically consistent. In order to respect consistency in sensor network deployment, the topological relationship must be observed. To ensure logical consistency in a model, some logical rules should be defined and then the validity of those rules must be verified in the model. For example a sensor node for monitoring the traffic in a city could not be placed on the top of a private property or in an area with a height lower than a predefined threshold. Another example could be poles in the city, which are supposed to be used for installing sensors. If they stand at the right side of the street but they are represented at the left side in 3D city model, our model is not consistent with the reality and optimization with this model would have a significant impact on the coverage. The maximum distance of coverage and communication between sensors should also respect logical rules when we try to place sensors in the environment.

In addition to the importance of accurate geometrical and topological representations of spatial information in 3D city models, semantic accuracy of spatial features is also essential for efficient optimization of a sensor network. Semantic accuracy deals with precise definitions of spatial, temporal, and thematic properties of each feature represented in 3D city models. Spatial features such as buildings, streets, poles, transportation objects, water bodies, and vegetation area must be accurately identified, classified and specified in the models. Thematic information must be semantically rich enough to allow consideration of all possible restrictions in the optimization process of sensor deployment in a given urban area.

Another important spatial data quality criterion that may have a significant impact on the coverage estimation of a sensor network is the completeness of spatial information in a 3D city model. As mentioned in the previous section, completeness of data may have different implications in a 3D city model including omissions, commissions and levels of detail (LOD) in the representation of an urban area. Open Geospatial Consortium (OGC) has adopted City Geography Markup Language (CityGML) as a standard for representation of 3D city models (Gröger et al. 2012). CityGML introduces five levels of detail to support multi-scale modeling of an urban area. In a 3D city model, the same object may be represented in different LOD simultaneously, enabling the analysis and visualization of the same object with regard to different degrees of resolution. Hence, spatial representation of an object may have some details in one level that can disappear in another level of detail. The roughest level, LOD0, is a two and a half dimension DTM and may be used for regional and landscape applications. LOD1 is the blocks model in the city or region, which represents buildings with flat roofs. In LOD2, roof structures in buildings are differentiated and vegetation objects may also be shown. City districts may be represented in LOD2. LOD3 contains architectural elements of buildings with detailed walls, roofs and balconies. Other urban structures such as detailed vegetation and transportation objects may appear in LOD3. LOD4 is a higher resolution representation of LOD3 with information on interior structures of 3D objects. Figure 6 depicts the five levels of detail in an urban area.

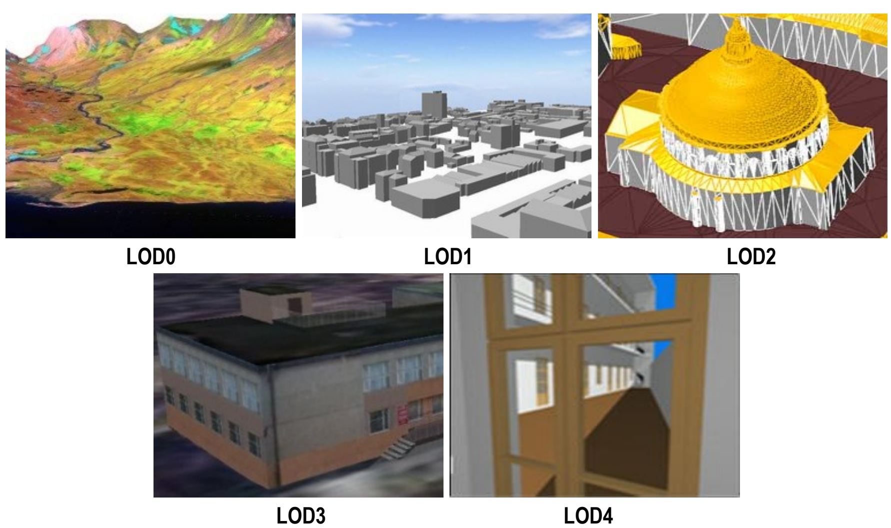


Figure 5.6: The five Levels of Detail in 3D city models (LOD) according to the Open Geospatial Consortium (Gröger et al. 2012)

In a sensor network deployment, the presence of some details directly affects the line-of-sight measurements and makes a specific target visible or obscured. For example, consider a building with balconies, which has been represented in LOD1. Consider also that there is a sensor placed on the top of such a building. As shown in Figure 5.7, the omission of the balconies in the 3D representation of the building will result in a complete coverage area compared to the case where the balconies are present in the 3D representation of the building.

Figure 5.7: The impact of completeness on the line-of-sight; Point B is visible but point A is invisible because of the presence of balconies in the building representation

Another important issue that has a significant impact on the sensor network optimization is the type of spatial representation of the real world. Vector and raster models are two fundamental representation methods of reality. Vector representations of the reality are often more accurate for spatial features with well-defined limits such as buildings and streets (Figure 5.8). However, most of the optimization algorithms are conceived based on raster representation of the environment since using raster models is less complex than vector models. In addition to the accuracy of representation of 3D objects, sensors could be more accurately positioned in vector maps. Indeed, an accurate determination of sensor positions in a raster representation of the space is more difficult. In addition, we need a very high resolution for 2D or 3D representation of the space in order to achieve the required precision. We think vector representation of the space such as in 3D city models will help to more precisely estimate spatial coverage of a sensor network, because visibility could be estimated more accurately in vector data. However, to our knowledge development of optimization algorithms for sensor networks using vector data models are poorly investigated and more research work is needed in the field.

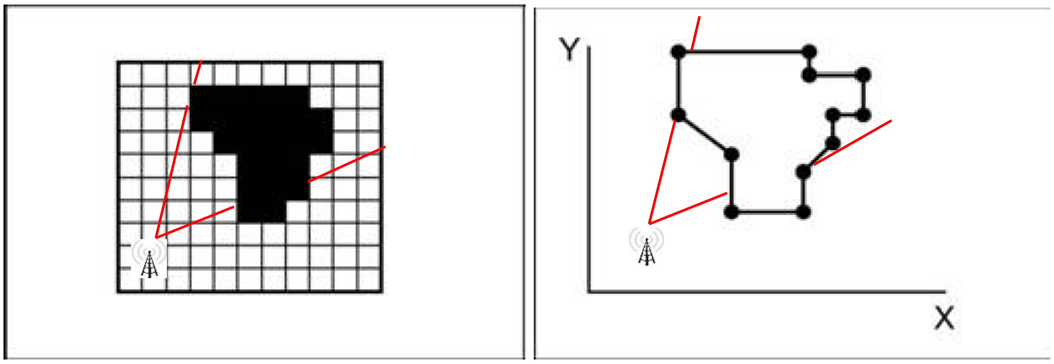


Figure 5.8: Raster versus vector representation of limits of a building; visibility and line-of-sigh can be computed more accurately using vector model.

5.6 Experimentation and Results

As discussed in the previous section, the quality of 3D city models can be evaluated based on different criteria. In this section, we carry out different experiments in order to show the impact of the map resolution and sensor configuration of a 3D model in the estimation of spatial coverage of a sensor network. For this purpose, we have prepared 5 maps with different resolutions of same area. Our goal is to investigate the impact of the positional accuracy and completeness of the dataset on the spatial coverage of a sensor network that will be introduced to the optimization algorithms. Here, the completeness implies the presence of some details in higher resolution maps that are omitted in the maps with lower resolution as discussed in previous sections. The resolution variation is from 500 cm (low resolution) to 50 cm (high resolution) and a map with 10 cm resolution is considered as the ground truth dataset to validate the results. The map dimension is 180 m by 170 m from an urban area in old Quebec City, Canada. Figure 5.9 depicts the 3D model of the study area.

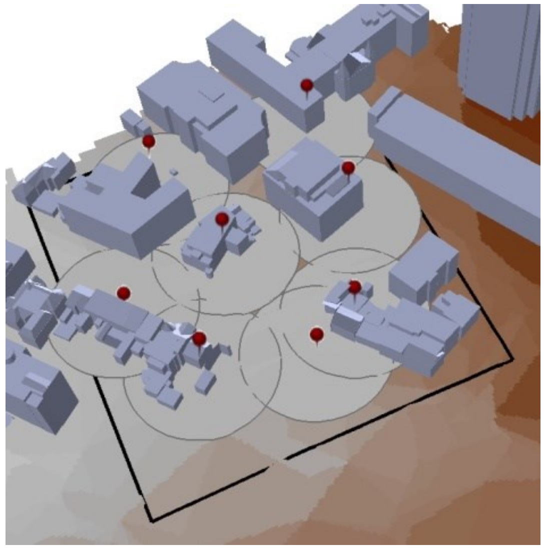


Figure 5.9: Sensor locations in a 3D city model, red points show the assumptive positions of 8 sensors in the environment and the circles depict their sensing area

This experiment consists of deploying eight sensors inside the study area, in order to obtain the best possible coverage by means of an optimization algorithm. It has been supposed that each sensor has a 35 meter sensing range, positioned one-meter height above the surface and has the ability to rotate 360 degrees horizontally and ±90 degrees vertically at its position.

As discussed in Section 5.3, two different types of optimization algorithms have been used for sensor network deployment: global and local approaches. In order to compare the sensitivity of the proposed optimization algorithms to the input dataset quality, we have chosen three optimization methods. For global approaches we have selected Covariance Matrix Adaptation Evolutionary Strategy (CMA-ES) and Simulated Annealing (SA). Among different stochastic optimization methods, these two methods were chosen because one (i.e. SA) is an example of a simple stochastic method and the other (i.e. CMA-ES) is an example of a more sophisticated method. Among local deterministic methods, enhanced VORonoi-based algorithm has been chosen in order to consider the geometrical characteristics of the study area. For all methods, each sensor placement optimization scheme was run 32 times, from which the average of each method was estimated. The initial positions of the sensors were determined randomly for each method.

To assess the sensitivity of the optimization methods with respect to the quality of data set, we conducted several experiments and present the results in Tables 5.2, 5.3 and 5.4. The experiments were carried out as follow:

1- First, for the purpose of the experiments, five maps with different resolutions from the same area were created;
2- For each map, we have conducted the optimization process using three methods as mentioned above;
3- Then, we computed the average and best coverage values for each map using each of those optimization methods (columns 2 and 3 in Tables 5.2, 5.3, and 5.4);
4- Next, the best sensor configuration is selected from each map resolution based on the best obtained coverage;
5- Finally, for each extracted best sensor configuration, the best coverage value calculated over the ground truth, and then the average coverage values were computed as well from 32 runs over the ground truth (columns 4 and 5 in Tables 5.2, 5.3, and 5.4).

It should be mentioned that in order to be able to compare the obtained results from the experiments, we applied the same sensing range for all sensors. The sensing area for each sensor was considered to be a crisp circle. In addition, the same algorithms were used for the determination of visible and nonvisible pixels and the coverage values for all the optimization methods. The performance of each method has also been evaluated by defining the same function for computing the viewshed inside the study area. Table 5.1 presents the configurations, which have been used for the experiments.

Table 5.1: Initial information on the sensor network used in our experimentation.

Method	*Num. of Sensors*	*Sensing range (m)*	*Num. of runs*	*Max. iteration*
CMA-ES	8	35	32	300
SA	8	35	32	4200
VOR	8	35	32	200

The results for CMA-ES have been reported in Table 5.2, SA in Table 5.3 and, enhanced VORonoi-based in Table 5.4.

Table 5.2: Results obtained from the CMA-ES method.

Resolution (cm)	*Avg. coverage (%)*	*Best coverage (%)*	*Best coverage from best configuration over 10cm resolution (%)*	*Average coverage over 10cm resolution (%)*
500	52.50	52.96	44.79	45.09
300	52.78	53.79	46.62	47.75
200	49.09	51.33	43.85	46.34
100	50.75	52.77	41.27	46.50
50	50.75	52.72	52.50	47.85

Table 5.3: Results obtained from the SA method.

Resolution (cm)	*Avg. coverage (%)*	*Best coverage (%)*	*Best coverage from best configuration over 10cm resolution (%)*	*Average coverage over 10cm resolution (%)*
500	45.50	51.73	47.40	40.06
300	45.16	49.98	46.10	40.97
200	42.59	48.95	49.09	41.28
100	45.75	48.07	42.33	41.85
50	44.97	47.55	47.12	43.35

Table 5.4: Results obtained from the enhanced VORonoi-based method.

Resolution (cm)	*Avg. coverage (%)*	*Best coverage (%)*	*Best coverage from best configuration over 10cm resolution (%)*	*Average coverage over 10cm resolution (%)*
500	45.55	47.19	43.14	42.21
300	47.83	51.07	45.87	45.37
200	40.06	43.82	42.43	40.51
100	44.38	45.77	44.25	42.83
50	46.59	48.16	45.64	44.32

The goal of the comparison between the three algorithms is not to determine which algorithm outperforms the other methods; our objective in this investigation is to discover the sensitivity of optimization algorithms to the quality of input datasets. Obtained results show that all three methods have good stability regarding the inaccuracy of the input dataset (between 5 meters to 50 centimeters resolutions). CMA-ES gives better coverage in all resolutions while SA and VOR have returned almost the same results. We presume that the reason is that CMA-ES is a more sophisticated optimization method, which derives a second order model of the objective function and explores more search space while SA is a simple stochastic optimization method, which randomly searches for a better solution in the search space. All three methods suffer the worst results when the resolution is 200 cm. The reason is related to the shape of objects in this study area. Comparing other resolutions, building details and obstacles begin to appear in 200 cm resolution, which causes more area to be obscured from sensor visibility. At lower resolutions, optimization algorithms perform better due to the disappearance of obstacles in the datasets. For higher resolutions, the scenario is changed; optimization algorithms perform better due to their inherent process to search the optimum when the pixel size is smaller. So, in this study area the resolution of 200 cm could be considered as a specific resolution.

Figure 5.10 compares the configuration of sensor positions and related coverage obtained over a map with 10cm resolution by using three optimization methods. The sensor positions obtained from CMA-ES give 52.50% coverage over the study area, while sensor configurations obtained from SA and VOR methods give 47.12% and 45.64% coverage respectively. The sensors have been positioned in almost the same places in all three algorithms with a few differences, which mean all algorithms have located almost the same places to place sensors with different input data quality.

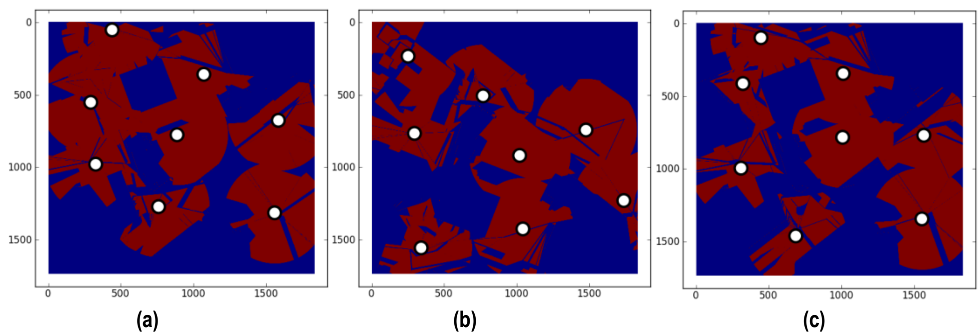


Figure 5.10: (a) Best sensor configuration over a map with 10 cm resolution from CMA-ES, (b) best sensor configuration over a map with 10 cm resolution from SA, and (c) best sensor configuration over a map with 10 cm resolution from enhanced VORonoi-based.

Figure 5.11 depicts the sensitivity of optimization methods with respect to the accuracy of input data. Each bar section shows the differences between the averages of coverage for each map and the coverage obtained by applying the best configuration of the sensor positions of all runs obtained from each map over the ground truth data. As shown in the figure the differences between the bars are not regular, because the best positions have been extracted from lower resolution and then applied over higher resolution to calculate the coverage. Hence, many obstacles have been ignored when the optimization algorithm was run over the lower resolution maps while they are considered to gain the coverage over the ground truth.

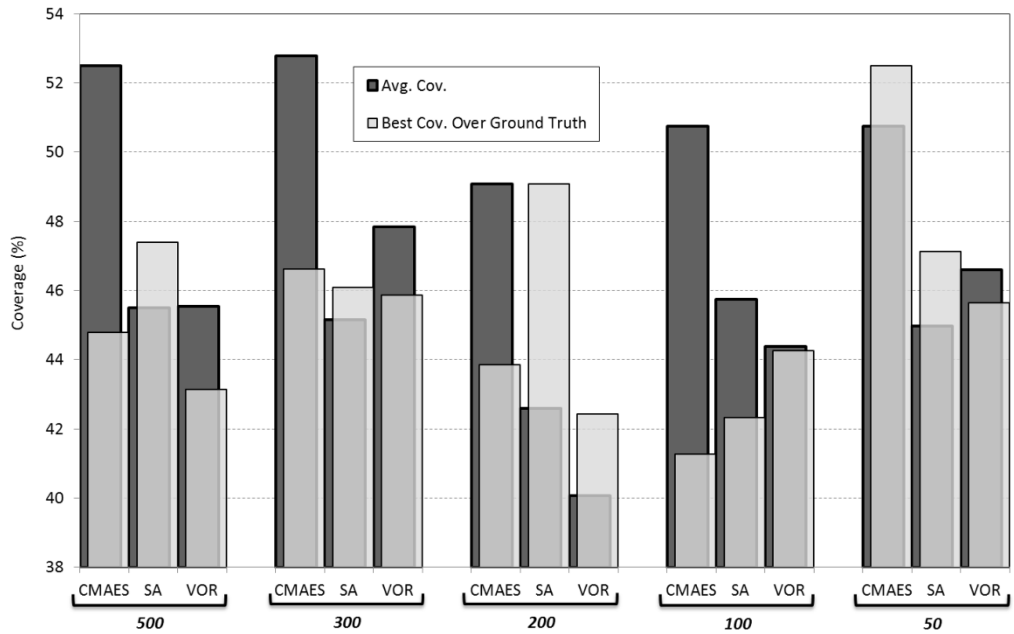


Figure 5.11: Comparison between average coverage obtained from different optimization methods over different map resolutions and best coverage obtained from different algorithms and map resolutions over ground truth dataset.

As illustrated in Figure 5.11, best coverage evaluated over 10 cm resolution map by using the best sensor configuration results has been influenced by the input data quality (resolution). To investigate this impact more accurately, we have compared the average of coverage for each map and the average of coverage evaluated over the ground truth data for all runs. Figure 5.12 shows sensitivity of different optimization algorithms with respect to the accuracy of input datasets. We can see from the figure that as the resolution of the maps becomes higher, the difference between the sensitivity of the optimization algorithms becomes smaller. We also observe that there is a peak in all curves at 200 cm resolution for all the optimization methods. As discussed earlier, this behavior is related to the worst coverage in that resolution, which does not exist in the evaluated coverage of ground truth data. In both figures 5.11 and 5.12, the biggest relative difference is seen on the CMA-ES in all resolutions. As mentioned earlier CMA-ES is a stochastic method, which explores more of the search space to find the optimum. Hence, it outperforms other approaches in terms of returning better results, but compared to the ground truth it returns farther outcomes. Among the three methods, VOR has less difference between the average coverage and the ground truth results. The reason is the deterministic nature of the VOR algorithm, which searches just specific predefined locations to find the optimum positions versus the stochastic characteristics of the CMA-ES and SA that explore almost randomly the search space.

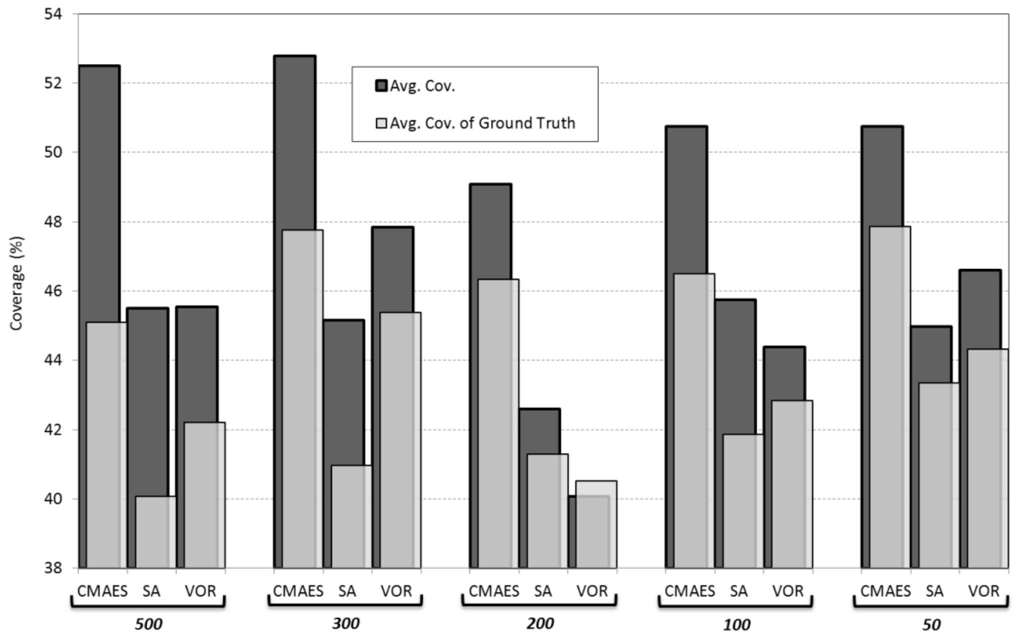


Figure 5.12: Comparison of differences between average coverage values obtained from original maps and the ground truth for three optimization methods.

Table 5.5 and Figure 5.13 show the results of the one-way analysis of variance (ANOVA) for three methods over maps with different resolutions. The one-way ANOVA is a technique to compare the means of samples to test whether those samples in two or more groups are drawn from the same population or not. The ANOVA produces a F-statistic, the ratio of the variance calculated among the means to the variance within the samples. If the group means are drawn from the same population, the variance between the group means should be lower than the variance of the samples. A higher ratio, therefore, implies that the samples were drawn from different populations (Hogg & Ledolter 1987). In this study, we used ANOVA to determine to what extent our evaluations of coverage over maps with different resolutions differ from each other. If we assume that all optimization methods should report the same coverage by using different resolution maps from the same study area, the F-statistic value allows us to determine to what extent coverage values are similar. In this case study, given that we have 5 groups (5 maps with different resolutions) and 32 sample per groups (32 runs for each map), the maximum F-statistics $F(x,y)$, with $x=4$ $(5-1)$ and $y=128$ $(32\times(5-1))$ for a probability level of 0.05, which allows us to test whether the results have a 95% chance of coming from the same statistical population, would be $F(4,128)=2.44$. So, a greater F-statistic refers to a higher sensitivity to the quality of the input dataset and vice versa. Table 5.5 indicates that the differences in the F-statistics results obtained by varying the resolution are significant for all methods, which confirms the sensitivity of all methods to the quality of input datasets. The lowest F-statistic 5.44 in Table 5.5 was obtained for SA, which indicates that the average coverage values from SA have more likely been obtained from the same populations, and therefore, SA, is less sensitive. The highest F-statistic is 229.6 for VOR, which is thus more sensitive to the quality of input data. The reason is that SA uses small absolute displacement to determine the optimum positions, which is not related to the resolution. The box plots of the different map resolutions for each method in Figure 5.14 indicate that the standard deviations with VOR are lower when compared to CMA-ES and SA, which indicates that results obtained from VOR algorithm are coherent in each run for the same map resolution. The reason is that VOR is a deterministic algorithm that uses the geometric structure of the environment, which is not changed by changing the initial sensor positions. So, applying the algorithm with different initial starting positions for sensors has less impact on the final results. Conversely, SA is a highly stochastic algorithm, which returns the highest standard deviation in the results for different runs on the same map resolution. CMA-ES is in-between these two algorithms, being more stable than SA, but still gives results with a higher standard deviation than VOR since it is also a stochastic optimization algorithm.

Table 5.5: F-statistic results from one-way ANOVA test.

	ANOVA F-statistic
CMA-ES	23.78
SA	5.44
VOR	229.6

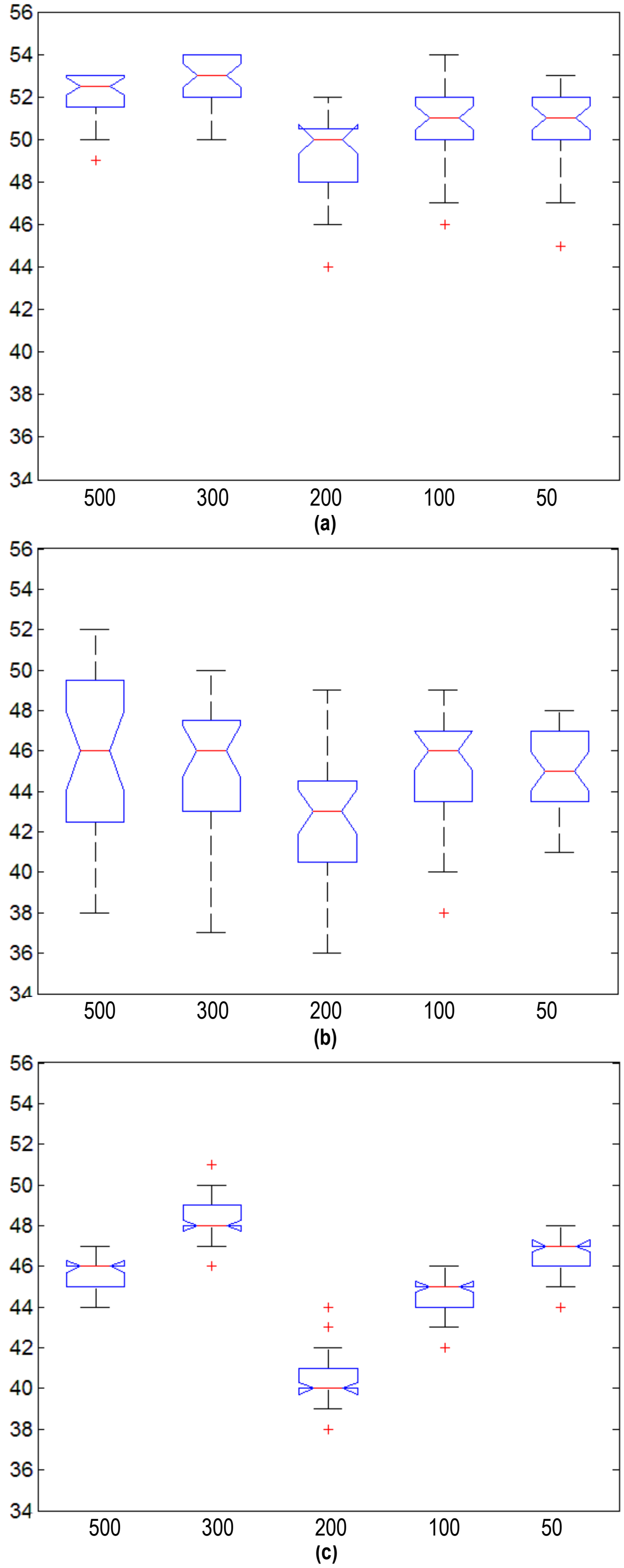


Figure 5.13: Box plot of one-way ANOVA test for different map resolutions for: (a) CMA-ES; (b) SA; (c) VOR methods

5.7 Conclusions

A survey on spatial data quality in 3D city models was conducted in this paper and a list of the most relevant elements of data quality for 3D models was proposed. The impact of 3D data quality elements on sensor placement has been determined by investigating their impact on the concepts of viewshed and line-of-sight. Positional accuracy and completeness were introduced as two important elements in sensor network deployment. The concepts of raster and vector data and their accuracies when are used as input in sensor network optimization algorithms were discussed. To examine the impact of 3D data quality on sensor network placement and calculated coverage, a comparison of the sensitivity between three optimization algorithms on the quality of input data was carried out. The algorithms, which were used in this investigation, were some global and local optimization methods with the novelty of integration of 3D models. The impact of data quality on final coverage and sensitivity of each method was studied by using different maps with different quality as input data to the optimization algorithms. Map resolutions range from 500 to 50 cm and a map of 10 cm resolution considered as the ground truth data.

The results show that all methods are generally stable with different resolution, which indicates that both global and local optimization algorithms are less sensitive to the quality of input data and return almost the same results. Regarding the algorithm of SA, it is less sensitive when compared to others; however the deviation is higher in the final coverage results. VOR has less deviation but it is a little more sensitive to the quality of input data. In terms of final coverage, CMA-ES performed better than the SA and enhanced VOR algorithms.

This research is not exhaustive in terms of studying the sensitivity of optimization algorithms with respect to all the data quality criteria. The research is however significant in terms of proposing a methodology for the assessment of the sensitivity of an optimization method with respect to the quality of spatial 3D models (ex. 3D city models). Throughout the paper, we have defined and illustrated the impact of some of the 3D data quality elements on the estimation of sensor network coverage. And finally, we have carried out experimentation, using three reliable optimization algorithms to illustrate more concretely the impact of the quality of 3D city models on the estimation of coverage in urban areas. Further investigations are required to define and analyze the impact of the spatial data quality for each quality criterion on the estimation of the spatial coverage of a given sensor network. It would be also interesting to carry out new experimentation on the quality assessment of 3D datasets with higher LODs for an urban area.

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CHAPTER 6

Conclusion and Perspectives

6.1 Summary

This thesis addressed the problem of coverage enhancement in sensor networks by developing a new optimization algorithm for sensor deployment in a given environment. The main contribution of this thesis was proposing a local context-aware optimization algorithm, which considered contextual information including real environment and the network space.

In Chapter 1, the context of research, the general and specific problems, the objectives of the thesis, and proposed methodology were presented. It was stated that this research aims at proposing a solution for sensor placement in the wireless sensor networks, in order to improve network coverage. Since spatial coverage of sensor networks is much related to the spatial distribution of the sensors in the environment, the deployment optimization algorithms have been used to distribute the sensors in the field so that as much possible coverage is obtained. Indeed, we noticed that it would be a complicated issue to consider the real environmental characteristics such as obstacles, spatial parameters, and relations. This means that we had to address several specific problems: the integration of spatial and environmental information, problem with the deployment optimization using a local approach, and problem with the uncertainty and data quality in spatial information that are used in the optimization process. The general hypothesis of this research work, which was introduced in Chapter 1, mentions that the integration of spatial and environmental information with the local optimization algorithms and geometric approaches can improve sensor networks coverage and provide an optimized deployment of sensor nodes in a real environment.

In Chapter 2, the background and state of the art concerning topics related to sensor network deployment was presented. First, a review of definitions and introductions of wireless geosensor networks, as well as their applications and technology was presented. Many of fundamental sensor network issues such as location, deployment, topology, connectivity, and spatial modeling were investigated in this chapter due to their direct impact on the network coverage. Then recent wireless sensor network problems and technical challenges such as sensor network topology, network control and connectivity, data fusion and processing, interface and data query, real time output, and sensor network deployment were discussed. A background of spatial modeling issues in deployment of wireless geosensor networks was provided, comprising an explanation of sensing models of sensors, communication models in networks, and preliminary geometric structures. Finally, the state of the art of core issues, including the spatial coverage and optimization algorithms in sensor network deployment was given. Two categories of global and local optimization approaches were investigated to illustrate how optimization algorithms may integrate in sensor network deployment. Especially, algorithms that use Voronoi diagram and Delaunay triangulation were intensively investigated. The literature review revealed that existing approaches are not fully adapted to the objective of this thesis due to oversimplifying the coverage problem and not considering the characteristics of the environment.

Chapters 3 to 5 include the original contribution of the thesis presented as articles published in or submitted to scientific journals. They present proposed solutions to the specific problems of this thesis and describe the approaches to achieve the objectives presented in Chapter 1.

In Chapter 3, a survey of the existing solutions for geosensor network optimization that use Voronoi diagram and Delaunay triangulation was conducted. Then a GIS based wireless sensor network coverage estimation and optimization approach was proposed. In the novel sensor network deployment approach the uncovered areas and holes in the sensing environment are detected and minimized using an optimization process, which relies on Voronoi diagram and Delaunay triangulation to identify sensing holes in the network and create an optimal arrangement of the sensors to eliminate these holes. The extended method proposes a more realistic approach by integrating spatial information in the optimization process.

In Chapter 4, which is the heart of this thesis, the problem of placing sensors to get optimum coverage was studied by investigating the concept of contextual information in sensor network. In order to develop the optimization method, a review of the optimization algorithms for sensor network deployment was given. Then, the concept of context was investigated in three levels including object (sensor), object environment, and physical environment. The different categories of context comprising locations, sensors, environmental objects, sensor mission, and software components were introduced as the most relevant CI elements in sensor network deployment. Contextual information modeling as well as context-aware functions and architectures in sensor network were identified and categorized concerning how sensor network deployment, applications, or services can effectively use the CI. The mentioned investigations led authors to propose a conceptual framework for sensor network deployment using Voronoi diagram and contextual information, which was the missing part of previous studies. Then, a novel local context-aware algorithm for optimization of sensor placement was developed based on the proposed conceptual framework. Given the developed algorithm, different case studies concerning different types of CI were investigated. Hence, the algorithm was tested in different situations such as taking into account obstacles and viewshed, restricted areas, the desirability of coverage, and environmental activities in the network.

In Chapter 5, the impact of the quality of spatial 3D city models on sensor network placement optimization was analyzed. First, various models and solutions of the sensor deployment optimization based on 3D city models were described. Then, the spatial data quality elements were presented and most relevant items related to 3D city models were further investigated alongside a discussion over their implications on sensor placement. Afterward, an analysis was done to show how the quality of 3D models affects the results of optimization methods. For further investigation the impact of raster and vector data representations and their accuracy was on the optimization algorithms were discussed. In order to validate the mentioned categories of data quality, several maps with different levels of quality were prepared and tested by running three well-known optimization algorithms over the datasets. Then, an evaluation of sensitivity of the optimization methods to the quality of input data was implemented.

6.2 Contributions and Discussions

The major contribution of this thesis is to integrate network and spatial environmental information in the process of sensor placement. The other contributions of this research, without which the major contribution would not have been possible, followed three specific objectives of the thesis, that is: 1) to define a framework in order to integrate spatial information in sensor network placement; 2) to develop a local context-aware optimization algorithm based on the proposed framework; 3) and to perform accuracy assessment and error propagation analysis. Therefore, according to the mentioned objectives, realistic models of the environment and the sensor networks are proposed. Thus, simplistic hypothesis are explicitly avoided in this work such as flat terrain, similar contextual conditions for all candidate locations, or similar data quality for the initial datasets. In other words, a flexible and applicable framework was extended to better handle sensor placement optimization with the purpose of handling it in the real world.

That being said, the purpose of the thesis was certainly not to overcomplicate the optimization process, but rather to find a flexible methodology that can locally accommodate all relevant information that would have an impact on sensor placement. To do so, a local optimization framework was introduced. Once this framework was defined for the particular problem at hand, defining the knowledge to use that appears relevant for the task at hand, the optimization can come up with different sensor placement configuration according to the various circumstances, environmental information, and/or sensor parameters encountered. Consequently, if there are any changes in sensor parameters or environment, the context-aware algorithm can simply take in new contextual inputs and regenerate a new sensor placement design adapted to the new situation. The main mentioned objectives, propositions, and perspectives are detailed in chapters 3, 4, and 5. Hence, the summary of contributions of the thesis is presented in the following subsections respectively.

6.2.1 Using Voronoi diagram to construct local geometrical structure of the network and environmental elements

It has been demonstrated in Chapter 3 that the Voronoi diagram and Delaunay triangulation has the potential to construct and manipulate a dynamic and kinetic data structure, in order to abstraction and modeling of sensor networks as well as their spatial relations and variations. However, their application is still limited when it comes to the determination and optimization of spatial coverage of sensor networks in complex environments (e.g., sensor networks with the presence of obstacles). To overcome the limitation of these methods, a novel approach based on Voronoi diagram was proposed in Chapter 3, which considered spatial information in sensor network deployment and coverage optimization such as line-of-sight, viewshed, visibility, network topology, nodes adjacency in the network, and the geometry of the network. Three basic problems in sensor placement, which were the coverage estimation, gap recognition, and filling uncovered areas by means of a deployment optimization algorithm, were discussed. Then, novel solutions were proposed based on Voronoi diagram to improve sensor network coverage. The proposed approach integrates the GIS facilities to the VECtor-based and VORonoi-based algorithms in sensor networks, and consequently realistic enhanced VECtor-based and enhanced VORonoi-based algorithms were extended. Applying the novel deployment approach, a considerable improvement in the spatial coverage of the sensor network was observed.

6.2.2 Developing a novel local context-aware optimization algorithm for sensor network deployment

The main contribution of Chapter 4 was adapting the concept of contextual information to the deployment optimization algorithms. It was also demonstrated that integrating local CI including contexts of physical environment and network parameters improves the performance of sensors deployment as well as giving a realistic estimate of the coverage. In addition, it was shown that using the local context-aware optimization algorithm allows to easily assess the feasibility of a sensor position in a real environment, such as the denial of placing a sensor in a restricted area, like a pond or on the top of a private building. The CI also definitely improved sensor placement in a local optimization. The process is to relocate a number of sensors that may be defined by the local optimization, while context-aware optimization helps to further refine the positions of sensors based on the current circumstances. This refining method is based on an existent sensor layout, but makes use of environmental and geometrical CI to improve the performance of deployment with some deterministic approaches. The outstanding advantage of the proposed context-aware algorithm was that it was designed independent of any specific CI. Thus, it is able to take into consideration different types of information based on specific network applications and tasks at hand. On the other words, realistic conditions might be added to the process of optimization as individual layers of information, which are supposed to be separately assessed by the algorithm, or a set of information, which define one consideration of many constraints. As an example that was presented in Chapter 4, one situation might be deploying sensors in an environment considering just different restricted areas. Another explained example was making sensor placement taking into account the desirability of coverage in an area where sensor placement was forbidden. In this situation, two sets of CI have been used as input information for the algorithm. Hence, an information fusion was happened on the background of the context-aware optimization algorithm. More sophisticated CI could be implemented to model more probable realistic situations using the information fusion.

6.2.3 Investigating the impact of spatial data quality on the sensor network deployment process

Most of the optimization algorithms consider that the spatial information used for sensor deployment is a perfect representation of the reality. However, spatial models are simplified representations of a complex reality, and hence they are inherently uncertain. In addition, optimization process may propagate these uncertainties. The main contribution of Chapter 5 was introducing the concept of data quality and categorized its relevant elements in terms of sensor network deployment. The next contribution was investigating the impact of the spatial data quality on the optimization of a sensor network deployment as well as spatial coverage in an urban area. Error propagation was investigated over different local and global optimization methods (CMA-ES, SA, and VOR). On the other words, the reaction of the stochastic (CMA-ES and SA) and deterministic (VOR) optimization methods was evaluated using different datasets with different quality levels.

6.3 Research perspectives and future works

The approach presented in this thesis has opened several new research avenues that could enhance the context-aware sensor network deployment to perform the coverage optimization. Possible future research perspectives include the followings:

Sensor network deployment may meet more complicated issues in terms of hole detection and coverage optimization. In some applications, such as military or security control, it is required that each point of the region is covered by at least k ($k>1$) sensors. Proposed solutions in Chapter 3 led us to solve this problem as the K-coverage sensor networks (Zhou et al. 2004; So & Ye 2005). The proposed algorithm can check the k-coverage for the area, but developing the algorithms to heal the holes in a given sensing area is still an open question.

Constructing sensor networks with various sensing range would be interesting and could greatly enhance the optimization outcomes. In reality, however, a sensor network could be composed of multiple types of sensors with different specifications, including their sensing range and sensing model (e.g., circular, ellipsoidal or irregular sensing model). Weighted Voronoi diagram is a solution in such cases to examine the coverage quality of the network. The achievements of this thesis are bringing on development of deployment strategies that include heterogeneous sensor networks.

Directional sensor networks (i.e., networks composed of sensor with limited and objective oriented field of views) offer the other aspect of monitoring a region of interest. Hence, coverage determination for these networks is a practical area of research and would be interesting to fulfil further investigation based on optimization methods, which were presented in this thesis.

We may also face some other problems in the deployment optimization such as sensor modeling, sensor capability variation, and information fusion. Sensor modeling is necessary because estimation and minimization of energy consumption are required for all deployed sensors. This way the longevity of the wireless sensor network can be maximized. The position of sensors may be also varied depends on sensor deployment model. Sensor capability variation is an important issue in realistic sensor deployment optimization, because sensor capabilities such as sensing range and communication range are affected by outside factors like terrain types, vegetation and elevation. For a realistic optimization, we need to take these factors into consideration. Information fusion presents a unique opportunity to further improve the overall deployment performance of the wireless sensor network. Instead of making decision based on binary conclusions, we can implement more sophisticated probable situations for all sensors locations in the network using some fusion functions. This shall further improve the deployment accuracy, detection capability, and at the same time increase the consistency of integrating the reality.

The approaches described in this thesis are rather focused on spatial aspects of optimization issues. It would be worth exploring other issues such as communication of sensors, limited sensor lifetime, and different communication range versus the transmission range. An interesting objective to be investigated would be handling with various performance issues and cost measures directly related to the task at hand. The performance criteria might be more than just region coverage; for example, it can be the time to detect or the time to intervene. Similarly, there might be different cost measures, such as sensor cost, battery cost, the cost of human intervention, and the cost of intrusion into a region of interest.

In the prototype developed local context-aware optimization algorithm, several case studies were implemented, but there are several different circumstances exist in the reality. It would be therefore interesting to implement the method over more complex applications. More situations could be introduced and validated as new types of spatial, temporal, and thematic CI in both categories of sensor network parameters and real environment. For example, the deployment optimization may run for performing the home security, industrial surveillance, and environmental monitoring.

This PhD thesis performed an investigation over the sensitivity of the applied optimization algorithm on the quality of the relevant dataset. There are concerns about testing all data quality criteria presented in Chapter 5 over the sample case studies. The research is however significant in terms of proposing a methodology for the assessment of the sensitivity of an optimization method with respect to the quality of spatial 3D models.

Thus, further investigations are required to define and analyze the impact of the spatial data quality for each quality criterion on the estimation of the spatial coverage of a given sensor network. It would be also interesting to carry out new experimentation on the quality assessment of 3D datasets with higher LODs for an urban area.

The proposed approaches developed in this thesis are rather implemented over raster datasets. It would be interesting to develop and apply the optimization algorithms based on vector data. Considering vector data includes the 3D coverage and may conduct better performance for the optimization algorithms.

This PhD thesis fulfilled a research investigation over the static sensor networks. Although, sensors may change their positions, finally they are fixed over their optimum positions according to the considerations of network coverage improvement. It would be therefore interesting to implement proposed methods over the mobile sensor networks.

Finally, this thesis has proposed the basis of a conceptual framework for sensor network deployment using the Voronoi diagram and contextual information, followed by a local optimization method. This is a very new concept, which opens many research opportunities for further works. In addition, new methods should be explored to carry out the sensor deployment considering the realistic contextual information using other optimization algorithms such as other statistic, heuristic, and stochastic approaches.

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