Towards Optimal Deployment of a Sensor Network in a 3D Indoor Environment for the Mobility of People with Disabilities

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Abstract

Mobility of people with disabilities is one of the most important challenges for their social integration. There have been significant effort to develop assistive technologies to guide the PWD during their mobility in recent years. However, these technologies have limitations when it comes to the navigation and guidance of these people through accessible routes. This is specifically problematic in indoor environments where detection, location and tracking of people, and other dynamic objects that may limit the mobility of these people, are very challenging. Thus, many researches have leveraged the use of sensors to track users and dynamic objects in indoor environments. However, in most of the described methods, the sensors are manually deployed. Due to the complexity of indoor environments, the diversity of sensors and their sensing models, as well as the diversity of the profiles of people with disabilities and their needs during their mobility, the optimal deployment of a sensor network is a challenging task. There exist several optimization methods to maximize coverage and minimize the number of sensors while maintaining the minimum connectivity between the sensor nodes in a network. Most of the current sensor network optimization methods oversimplify the environment and do not consider the complexity of 3D indoor environments. In this paper, we propose a novel 3D local optimization algorithm based on a geometric spatial data structure that takes into account some of these complexities for the purpose of helping PWD in their mobility in 3D indoor environments such as shopping centers, museums and other public buildings.

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1 Introduction

Social participation of people with disabilities (PWD) is one of the challenging problems in our society. According the United Nation's convention for PWD "persons with disabilities may include those who have long-term physical, mental, intellectual or sensory impairments which in interaction with various barriers may hinder their full and effective participation in society on an equal basis with others" [6]. According to a recent publication by Statistics Canada (2013), 13.7% of the population aged over 15 years live with a type of disability.

Based on the International Classification of Functioning (ICF) and the Disability Creation Process (DCP) model [5], social participation of PWD results from the interactions between their personal characteristics and the physical and social environmental factors. Most of the urban infrastructures and services are designed for people without any disability and do not consider the specific needs of PWD. This significantly limits the mobility of PWD and their social participation (e.g., going to work, the market, the museum, etc.). Mobility is a life habit that significantly influences other human life habits [5], and depending on the context, mobility may include movements such as postural transfers (e.g., from a chair to a bed) or moving from a point to another during diverse daily activities (walking, working or playing, driving a car, and using public transportation).

With the expansion of urban development and the construction of complex city infrastructures such as road networks, public buildings, shopping malls, airports, and museums, there is an increasing need for assistive navigation technologies to help PWD in their mobility. Efficient navigation in such environments require accurate and up-to-date information on the accessibility of those environments including information on possible obstacles and facilitators for the mobility of PWD. For this purpose, sensor networks provide interesting potentials to locate and track the dynamics of indoor environments and provide timely information to PWD during their navigation.

In recent years, a variety of sensor types has been developed and used for monitoring and measuring dynamic environments. For instance, in a mobility context, the majority of sensors have been used for positioning and tracking of people and moving objects. Tracking sensors are generally embedded in the environment and constitute a sensor network. These sensors must be deployed in the environment and have the best configuration to maximize the coverage and guarantee their connectivity and minimize the cost (optimal number of sensors and their types). There exist several optimization methods to maximize coverage and minimize the number of sensors while maintain the minimum connectivity between the sensor nodes in a network. Most of the current sensor network optimization methods oversimplify the environment and do not consider the complexity of 3D indoor environments. In this paper, we propose a novel 3D local optimization algorithm based on a geometric spatial data structure that takes into account some of these complexities for the purpose of helping PWD in their mobility in 3D indoor environments such as shopping centers, museums and other public buildings.

The remainder of this paper is organized as follows: Section 2 presents a brief literature review on sensor network deployment in indoor environments for mobility purposes and highlights their strengths and limitations. In section 3, the methodology of the proposed local deployment approach will be elaborated with consideration of indoor complex environment models and mobility applications. Then in section 4, an experiment will be conducted in an indoor environment. Finally, the results will be discussed in the last section.

2 Related works

Optimal deployment of a sensor network in a complex indoor environment is a challenging task. This complexity becomes even more challenging if we consider the diversity of sensor types and their sensing models as well as the specificity of the requirements for each application. With network deployment optimization methods, we try to maximize the coverage of the network and minimize the cost of the network and energy consumption for each node while maintaining a minimum connectivity between nodes in a wireless sensor network (WSN) [2].

The WSN coverage problem has been studied intensively in the last decade. A sensor coverage can be either target-based or area-based. In some WSN applications, detecting target points such as buildings, doors, flags and boxes are desired, while in area-based coverage, the aim is to detect mobile targets such as intruders in a given area [7]. Covering target points, instead of the whole area, is addressed in the target-based coverage problem, whose purpose is to cover the maximum number of target points. In the area-based coverage problem, which is used in this research, the objective is to obtain the maximum region covered by sensors, which is usually evaluated as the ratio of the covered area to the whole area [8].

Several methods have been proposed for optimal deployment of sensor networks based on the maximum coverage criteria [3]. These methods are either global or local and can be deterministic or stochastic. Particle Swarm Optimization (PSO) algorithms [9], and Covariance Matrix Adaptation Evolution Strategy (CMA-ES) [2] are among global approaches for sensor network deployment optimization. These methods apply a global objective function that is optimized for the whole network. In local algorithms such as Virtual force-based methods [11], and Voronoi algorithms [10], the optimization is done locally by changing the position of sensors with respect to the local context and the configuration of the neighboring algorithms. Both global and local algorithms can be considered as stochastic or deterministic depending on the definition of the sensing model of the sensors.

Most of the sensor network optimization methods use 2D raster representations of the environment [2] or voxel representation for 3D environments [4], which limit their precision and efficiency. This is because raster and voxel representations need a regular partition of the whole space even for homogeneous areas (i.e. the unoccupied pixels or voxels). Moreover, the raster-based models cannot be used to represent precisely indoor environments as they are constrained by their resolutions.

Voronoi based algorithms have attracted much attention in the research community interested in optimal sensor networks deployment, specially for its interesting spatial and topological properties for defining and manging sensor networks. For instance, [3] have proposed a local context-aware sensor network deployment algorithm based on 2D Voronoi diagrams for urban environments. In the latter work, Voronoi diagram is also used to define a movement strategy for sensors to heal the coverage holes of a sensor network where the environment was represented using a 2.5D digital surface model (DSM). In [1], a sensor coverage estimation method has been proposed based on precise 3D vector representation of the environment. Here in this paper, we propose to take advantage of 3D Voronoi diagrams and the vector-based representation of the indoor environment to develop a local sensor network optimization algorithm for indoor environments in order to support the navigation of PWD.

2.1 Methodology

For the deployment of a sensor network in an indoor environment, we propose a local context aware optimization algorithm based on 3D Voronoi diagrams. For this purpose, we assume that sensors can be deployed mainly on the walls and ceilings. Building floors are considered as target areas to be covered where navigation activities are expected. As mentioned previously, the sensing model (binary or probabilistic), sensor orientation (omni-directional or directional) and other sensor characteristics such as observation angle and distance ranges, should also be defined. In this paper, we consider an omni-directional sensor model for our sensor network.

In addition to sensor characteristics, the 3D indoor environment needs to be represented in details for optimal sensor network deployment. We also need to consider the presence of other objects embedded in the indoor environment that may affect coverage information (e.g., presence of a column or other permanent obstacles in the environment). Hence, we need a data structure that supports precise representation of the indoor environment and allows semantic specification of all its components. For modeling 3D indoor environments, we consider to benefit from the potentials of 3D IndoorGML for the representation of such environments.

3D IndoorGML is an extension of CityGML (Level of details (LoD) 4) that provides semantical, topological, and spatial information of objects and services. Like CityGML LoD4, IndoorGML is an open standardized data model of interior space of 3D buildings that includes core modules, appearance modules, and thematic modules. The main structure of IndoorGML divides the indoor space into multi-spaces called cells, and the intersected area of two neighboring cells is called boundary surface. IndoorGML uses two related spaces to model indoor environments: (1) primal space is the geometrical representation of cells and boundary surfaces, (2) dual space is the Node Relationship Graph representation of cells and boundary surfaces, which respectively corresponds to nodes and edges. Generally, IndoorGML contains connection spaces (e.g., doors), anchor spaces (e.g., building exits), general spaces (e.g., rooms) and transition spaces (e.g., passages). In contrast, CityGML includes boundary surfaces, rooms, openings, and closure surfaces (e.g., the space between the kitchen and the living room is a virtual surface called closure surface).

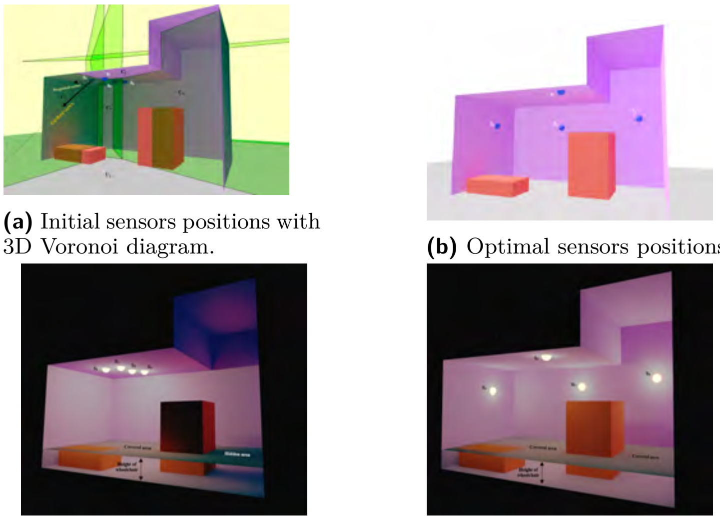
Algorithm 1: 3D Voronoi deployment algorithm.

```
input     : n omni-directional cameras Si(xi, yi, zi)
output    : (Xi, Yi, Zi) optimal solutions
objective : Maximizing the coverage of cameras network

Initialize: Random distribution of the cameras on deployment planes
  (walls/ceilings)   Compute initial sensor network coverage ;

while stop_criterion do
  | 3D_Voronoi(Si,...,Sn);
  | for i ← 1 to n do
  |   | Movement strategy(Si);
  |   | {
  |   | 1- choose the farthest vertex in the same direction of path segments;
  |   | 2- project the movement vector on sensor deployed plane;
  |   | 3- if movement vector has intersection with obstacle, keep a given distance
  |   |    between sensors and obstacle;
  |   | }
  |   | Update sensor network coverage (Si);
  |   | {
  |   | 1- choose the movement amount based on the coverage improvement
  |   | }
  | end
end
```

The objective of sensors deployment in such environment is the maximization of the covered areas of path segments that include floors with the height of a typical pedestrian who navigates in the indoor environment. Our aim with placing sensors in such environment is to inform the PWD of the dynamics of those environments and also to guide them safely towards their final destination.



(a) Initial sensors positions with 3D Voronoi diagram.
(b) Optimal sensors positions.
(c) Initial coverage area.
(d) Optimal coverage area.

Figure 1 Deployment of 4 cameras in an indoor environment with obstacles.

The proposed algorithm for deployment of sensors (the cameras in this research) is inspired from a local 2D Voronoi approach presented in [10]. This method uses a Voronoi diagram for the representation of a sensor network and the relations between sensors. We extend that method to 3D space and use a 3D Voronoi diagram for the representation of sensors and their topological relations in the sensor network. Thus, in the proposed algorithm, we first create the 3D Voronoi structure using sensors as the generators of the 3D cells in algorithm 1. In each iteration, we move the sensors towards the farthest vertex of their Voronoi cell to reduce the overlapping coverages and to better cover the target areas. It should be noted that the motion of each sensor needs to be done on the wall or ceiling. Therefore, the motion vector of each sensor is projected on the sensor position plane and the sensor is moved in this direction towards its new position. In the case of the presence of a permanent obstacle in the moving direction we need to keep the sensor away from the obstacle with a given distance so that its sensing field is maximized.

3 Experiment and results

In this experiment, we assume that four cameras are deployed in a semi-complex indoor environment where the ceiling is composed of two sections with different heights. We assume that the cameras have a spherical sensing model with a defined range of view. Each camera has an initial position (x, y, z) and is located on the ceiling or walls.

The environment model represents a semi-complex three-dimensional indoor environment and contains a few static obstacles (Figure 1a). The 3D indoor model is stored using IndoorGML and the geometric information can be easily extracted and analyzed if needed. In our case study, the indoor environment model consists of 8 segments (faces) and includes two obstacles. The goal of this experiment is to reach the maximum coverage of the floor that can be used as a part of path for the mobility of a PWD (e.g., a person using a wheelchair) from an initial configuration of cameras (Figure 1c). Then, the objective function is defined in a way that the floor is covered with a height corresponding to the height of a person using a wheelchair for her/his mobility (Figures 1b and 1d).

4 Conclusions

Navigation of PWD is a complex task in indoor environments. These people need assistive technologies to help them in their mobility and to guide them through their path by providing them directions and information on the accessibility of their path. Wireless sensor networks provide interesting opportunities to help these people with their navigation in indoor environments. However, optimal deployment of a sensor network in a 3D indoor environment is a very challenging problem given the complexity of the indoor environments and the presence of diverse obstacles as well as the diversity of sensors and their sensing models. Here in this paper, we have presented a new local optimization algorithm integrating 3D Voronoi diagrams for sensor network representation and 3D IndoorGML for the representation of the 3D indoor environments. We have defined an iterative algorithm for sensors movement that allows the improvement of the overall coverage of the sensor network. Finally we have presented a concept proving experiment with promising results. This work is part of an ongoing research project. We plan to carry out more comprehensive experiments in the near future to test and improve the proposed algorithm.

References

1 A Afghantoloee, S Doodman, F Karimipour, and M A Mostafavi. Coverage Estimation of Geosensor in 3d Vector Environments. *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, 40(2):1, 2014.

2 Vahab Akbarzadeh, Christian Gagné, Marc Parizeau, Meysam Argany, and Mir Abolfazl Mostafavi. Probabilistic sensing model for sensor placement optimization based on line-of-sight coverage. *IEEE Transactions on Instrumentation and Measurement*, 62(2):293–303, 2013.

3 Meysam Argany. *Development of a GIS-Based Method for Sensor Network Deployment and Coverage Optimization.* PhD thesis, Universit{é} Laval, 2015.

4 Francois-Michel De Rainville, Christian Gagné, and Denis Laurendeau. Automatic Sensor Placement For Complex Three-dimensional Inspection and Exploration.

5 Patrick Fougeyrollas, René Cloutier, Hélène Bergeron, Ginette St-Michel, Jacques Côté, Marcel Côté, Normand Boucher, Kathia Roy, and Marie-Blanche Rémillard. *The Quebec classification: Disability creation process.* Qu{é}bec RIPPH/SCCIDIH,, 1998.

6 Melvyn Colin Freeman, Kavitha Kolappa, Jose Miguel Caldas de Almeida, Arthur Kleinman, Nino Makhashvili, Sifiso Phakathi, Benedetto Saraceno, and Graham Thornicroft. Convention on the Rights of Persons with Disabilities, 2015.

7 M Amac Guvensan and A Gokhan Yavuz. On coverage issues in directional sensor networks: A survey. *Ad Hoc Networks*, 9(7):1238–1255, 2011.

8 Chi-Fu Huang and Yu-Chee Tseng. The coverage problem in a wireless sensor network. *Mobile Networks and Applications*, 10(4):519–528, 2005.

9 Raghavendra V Kulkarni and Ganesh Kumar Venayagamoorthy. Particle swarm optimization in wireless-sensor networks: A brief survey. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 41(2):262–267, 2011.

10 Guiling Wang, Guohong Cao, and Thomas F La Porta. Movement-assisted sensor deployment. *IEEE Transactions on Mobile Computing*, 5(6):640–652, 2006.

11 Yao Zou and Krishnendu Chakrabarty. Sensor deployment and target localization based on virtual forces. In *INFOCOM 2003. Twenty-Second Annual Joint Conference of the IEEE Computer and Communications. IEEE Societies*, volume 2, pages 1293–1303. IEEE, 2003.