Déploiement optimal de réseaux de capteurs dans des environnements intérieurs en support à la navigation des personnes à mobilité réduite

Thèse

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Résumé

La participation sociale des personnes ayant une incapacité (PAI) est l'un des enjeux majeurs de notre société. La participation sociale des PAI est influencée par les résultats des interactions entre les facteurs personnels et les facteurs environnementaux (physiques et sociaux). L'une des activités quotidiennes les plus importantes en milieu urbain est la mobilité, ce qui est fondamental pour la participation sociale des PAI. L'environnement urbain est composé des infrastructures et des services principalement conçus pour les personnes sans incapacités et ne prend pas en compte les besoins spécifiques des PAI. Dans ce contexte, la conception et le développement des environnements intelligents peuvent contribuer à une meilleure mobilité et participation sociale des PAI grâce à l'avancement récent de technologie de l'information et de télécommunication ainsi que de réseaux de capteurs.

Cependant, le déploiement de réseaux de capteurs en tant que technologie d'assistance pour améliorer la mobilité des personnes n'est conçu que sur la base des modèles trop simplistes de l'environnement physique. Bien que des approches de déploiement de réseaux de capteurs aient été développées ces dernières années, la plupart d'entre elles ont considéré le modèle simple des capteurs (cercle ou sphérique dans le meilleur des cas) et l'environnement 2D, (sans obstacle), indépendamment des besoins des PAI lors de leur mobilité.

À cet égard, l'objectif global de cette thèse est le déploiement optimal de réseau de capteurs dans un environnement intérieur pour améliorer l'efficacité de la mobilité des personnes à mobilité réduite (PMR). Plus spécifiquement, nous sommes intéressés à la mobilité des personnes utilisatrices de fauteuil roulant manuel. Pour atteindre cet objectif global, trois objectifs spécifiques sont identifiés. Premièrement, nous proposons un cadre conceptuel pour l'évaluation de la lisibilité de l'environnement intérieur pour les PMR, afin de déterminer la méthode appropriée pour évaluer les interactions entre les facteurs personnels et les facteurs environnementaux (par exemple, pentes, rampes, marches, etc.). Deuxièmement, nous développons un algorithme d'optimisation locale basé sur la structure Voronoi 3D pour le déploiement de capteurs dans l'environnement intérieur 3D pour s'attaquer à la complexité de la structure de l'environnement intérieur (par exemple, différentes hauteurs de plafonds) afin de maximiser la couverture du réseau. Troisièmement, pour aider la mobilité des PMR, nous développons un algorithme d'optimisation ciblé pour le déploiement de capteurs multi-types dans l'environnement intérieur en tenant compte du cadre d'évaluation de la lisibilité pour les PMR.

La question la plus importante de cette recherche est la suivante : quels sont les emplacements optimaux pour un ensemble des capteurs pour le positionnement et le guidage des PMR dans l'environnement intérieur complexe 3D. Pour répondre à cette question, les informations sur les caractéristiques des capteurs, les éléments environnementaux et la lisibilité des PMR ont été intégrés dans les algorithmes d'optimisation locale pour le déploiement de réseaux de capteurs multi-types, afin d'améliorer la couverture du réseau et d'aider efficacement les PMR lors de leur mobilité. Dans ce processus, le diagramme de Voronoi 3D, en tant que structure géométrique, est utilisé pour optimiser l'emplacement des capteurs en fonction des caractéristiques des capteurs, des éléments environnementaux et de la lisibilité des PMR. L'optimisation locale proposée a été mise en œuvre et testée avec plusieurs scénarios au Centre des congrès de Québec. La comparaison des résultats obtenus avec ceux des autres algorithmes démontre une plus grande efficacité de l'approche proposée dans cette recherche.

Abstract

Social participation of people with disabilities (PWD) is one of the challenging problems in our society. Social participation of PWD is influenced by results from the interactions between personal characteristics and the physical and social environments. One of the most significant daily activities in the urban environment is mobility which impacts on the social participation of PWD. The urban environment includes infrastructure and services are mostly designed for people without any disability and does not consider the specific needs of PWD. In this context, the design and development of intelligent environments can contribute to better mobility and social participation of PWD by leveraging the recent advancement in information and telecommunications technologies as well as sensor networks.

Sensor networks, as an assistive technology for improving the mobility of people are generally designed based on the simplistic models of physical environment. Although sensor networks deployment approaches have been developed in recent years, the majority of them have considered the simple model of sensors (circle or spherical in the best case) and the environment (2D, without obstacles) regardless of the PWD needs during their mobility.

In this regard, the global objective of this thesis is the determination of the position and type of sensors to enhance the efficiency of the people with motor disabilities (PWMD) mobility. We are more specifically interested in the mobility of people using manual wheelchair. To achieve this global objective, three specific objectives are demarcated. First, a framework is developed for legibility assessment of the indoor environment for PWMD to determine the appropriate method to evaluate the interactions between personal factors with environmental factors (e.g. slops, ramps, steps, etc.). Then, a local optimization algorithm based on 3D Voronoi structure for sensor deployment in the 3D indoor environment is developed to tackle the complexity of structure of indoor environment (e.g., various ceilings' height) to maximize the network coverage. Next, a purpose-oriented optimization algorithm for multi-type sensor deployment in the indoor environment to help the PWMD mobility is developed with consideration of the legibility assessment framework for PWMD.

In this thesis, the most important question of this research is where the optimal places of sensors are for efficient guidance of the PWMD in their mobility in 3D complex indoor environments. To answer this question, the information of sensors characteristics, environmental elements and legibility of PWMD have been integrated into the local optimization algorithms for multi-type sensor networks deployment to enhance the network coverage as well as efficiently help the PWMD during their mobility. In this process, Voronoi diagram as a geometrical structure is used to change the sensors' location based on the sensor characteristics, environmental elements and legibility of PWMD. The proposed local optimization is implemented and tested for several scenarios in Quebec City Convention Centre. The obtained results show that these integration in our approach enhance its effectiveness compared to the existing methods.

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Avant-propos

Cette thèse a été préparée comme une thèse par articles et comprend trois articles soumis dans des revues avec comité de lecteur. L'auteur de cette thèse, Ali Afghantoloee, est l'auteur principal des articles. Les coauteurs sont le professeur Mir Abolfazl Mostafavi, directeur de recherche, le professeur Geoffrey Edwards, codirecteur de recherche, ainsi que le Dr Amin Gharebaghi et le professeur Farid Karimipour comme collaborateur. La contribution de l'auteur dans ces manuscrits a consisté à la réalisation de toutes les expérimentations, la préparation et l'analyse des données et la rédaction des articles, qui ont été révisées et améliorés par les coauteurs avant de leur soumission aux revues scientifiques.

Les articles de revues issus de cette thèse sont les suivants :

Articles de journaux :

1. **Afghantoloee, Ali**; Mir Abolfazl Mostafavi; Geoffrey Edwards; Amin Gharebaghi. Personalized Legibility of an Indoor Environment for People with Motor Disabilities: A New Framework. *ISPRS Int. J. Geo-Information* 2020, *9*, 649.

2. **Afghantoloee, Ali**; Mir Abolfazl Mostafavi. A Local 3D Voronoi-Based Optimization Method for Sensor Network Deployment in Complex Indoor Environments. *Sensors*, 2021, 21(23), 8011.

3. **Afghantoloee, Ali**; Mir Abolfazl Mostafavi. A purpose-oriented 3D Voronoi algorithm for deployment of a multi-type sensor network in 3D complex indoor environments in support of the mobility of people with motor disabilities. *Geo-Spatial Information Science*, 2022 (submitted).

Deux autres articles de conférence (articles courts) qui ont été publiés sur les travaux de cette thèse sont.

Courts articles de conférence :

1. **Afghantoloee, Ali**; Mir Abolfazl Mostafavi. Towards Optimal Deployment of a Sensor Network in a 3D Indoor Environment for the Mobility of People with Disabilities (Short Paper). *In Proceedings of the 10th International Conference on Geographic Information Science (GIScience 2018)*, **2018**.

2. **Afghantoloee, Ali**; Farid Karimipour; Mir Abolfazl Mostafavi. A novel method for probabilistic coverage estimation of sensor networks based on 3D vector representation in complex urban environments. *In Proceedings of the International Conference on Geographic Information Science (GIScience 2016)* **2016**.

Introduction

1.1. Contexte de la recherche

La participation sociale des personnes ayant une incapacité (PAI) est l'un des problèmes majeurs de notre société. Selon la définition de la convention des Nations unies, « *les personnes en situation de handicap peuvent inclure celles qui ont des déficiences physiques, mentales, intellectuelles ou sensorielles à long terme qui, en interaction avec divers obstacles, peuvent entraver leur participation pleine et effective à la société sur un pied d'égalité avec les autres* » (Freeman et al., 2015). Selon une publication récente de Statistique Canada (de Vries McClintock et al., 2016), 22 % de la population âgée de plus de 15 ans vit avec un type de problèmes d'incapacités. Une étude récente sur les limitations d'activités, les maladies chroniques et le vieillissement suggèrent que 33 % des résidents du Québec souffrent de certaines formes de limitations fonctionnelles et que ce pourcentage augmente à plus de 57 % chez les personnes âgées de 65 ans et plus (Statistic, 2016).

La participation sociale des PAI est influencée par les résultats des interactions entre les caractéristiques personnelles et les environnements physique et social tels que spécifiés au sein des définitions de la classification internationale du fonctionnement (CIF) et du modèle du processus de production du handicap (PPH) (Fougeyrollas et al., 2019). L'environnement urbain comprend des infrastructures et des services conçus pour des personnes sans handicaps et la plupart du temps ne tient pas compte des besoins spécifiques des PAI. L'hétérogénéité des profils des PAI et la diversité des facteurs environnementaux conduisent à des interactions homme-environnement complexes qui limitent leurs activités quotidiennes. Ainsi, afin de créer l'égalité des chances entre les personnes, l'accessibilité aux lieux urbains doit être améliorée pour tous les individus de la société.

L'une des activités quotidiennes les plus importantes en milieu urbain est la mobilité, ce que nous sommes intéressés à étudier dans cette recherche. Elle a un impact significatif sur la participation sociale des PAI, en particulier des personnes à mobilité réduite (PMR), en relation avec les différents aspects sociaux de leur vie (par exemple, aller au travail, au marché, au musée, etc.). La mobilité peut être définie à différentes échelles, y compris la locomotion comme la marche quotidienne ou les transferts posturaux (par exemple, d'une chaise à un lit), les activités de travail ou de jeu, la conduite automobile et l'utilisation des transports en commun. La mobilité est une habitude de vie qui influence significativement les autres habitudes de vie humaine et qui se définit comme « une *activité quotidienne ou un rôle social valorisé par la personne ou son contexte socioculturel en fonction de ses caractéristiques (âge, sexe, socio-identité culturelle, etc.)* » (Fougeyrollas et al., 1998). La définition générale de la mobilité humaine est le déplacement d'une personne d'un point à un autre (Kirby et al., 2002). Ce déplacement est limité par les capacités humaines et l'environnement physique. La tâche de mobilité pour une personne est une tâche complexe qui est affectée par l'environnement aux multiples facettes et les incapacités de l'individu comme la capacité de mobilité, la perception, la mémoire et la cognition. Afin de satisfaire les personnes dans leur mobilité, des informations et des technologies appropriées pourraient être utilisées pour aider les personnes au cours de leur navigation.

Avec le développement d'infrastructures urbaines complexes telles que les bâtiments publics, centres commerciaux, aéroports et musées (environnements intérieurs) ainsi que les réseaux routiers, la compréhension et la représentation mentale de l'environnement physique sont devenues plus difficiles pour la population. Par conséquent, le recours à un système d'assistance à la navigation ou à l'aide d'autres personnes pour naviguer dans ces milieux devient inévitable. En particulier, comprendre les environnements intérieurs complexes et 3D dépasse la capacité de la mémoire humaine et conduit à la confusion lors de la navigation (O'Neill, 1991).

Pour évaluer la compréhension de la complexité des environnements intérieurs à l'appui de la tâche de mobilité, la lisibilité de l'espace a été utilisée comme l'un des indicateurs de complexité de ces environnements durant ces dernières années (Li & Klippel, 2016). En effet, une évaluation de lisibilité personnalisée peut fournir des indicateurs qui conduisent à de meilleures conceptions et au développement d'environnements plus accessibles et plus lisibles à l'aide de technologies d'assistance qui peuvent permettre aux PMR de mieux se déplacer et interagir avec leur environnement intérieur. Cette évaluation permet aux architectes et aux ingénieurs d'obtenir une meilleure estimation du niveau de lisibilité et facilite les actions ultérieures pour augmenter la lisibilité des environnements intérieurs, en particulier pour les PMR. De plus, les techniques d'assistance peuvent être conçues pour faciliter la mobilité des PMR en abordant le niveau de mauvaise lisibilité.

La lisibilité d'un environnement intérieur ou extérieur est définie comme « *la facilité avec laquelle ses parties peuvent être organisées en un motif cohérent* » (Lynch, 1960). La lisibilité facilite la construction d'une carte cognitive, c'est-à-dire d'une carte mentale de l'environnement qui est utilisée pour la tâche de navigation. Plusieurs analyses de lisibilité et de complexité des environnements physiques ont également été rapportées ces dernières années à l'appui des applications de navigation (Belir & Onder, 2013; Günecs, 2018; Li and Klippel, 2016). En général, les facteurs de lisibilité abordés comprenaient : 1) l'accès visuel, 2) le niveau de connectivité et 3) le niveau de complexité de l'aménagement de l'environnement, qui sont principalement axés sur la structure géométrique de l'environnement. Outre les facteurs environnementaux, la lisibilité des personnes, en particulier les PMR, dépend également de facteurs personnels, y compris leurs capacités et leurs expériences qui doivent être prises en compte pour sa personnalisation.

L'idée d'intégration des éléments environnementaux et personnels pour aider les PMR dans leurs efforts de déplacements a été proposée par le projet MobiliSIG. Ce projet a été lancé en 2013 pour développer une technologie d'assistance pour la navigation des PMR à Québec (Gharebaghi & Mostafavi, 2016). L'objectif de MobiliSIG est d'évaluer l'accessibilité des trottoirs et des passages pour piétons dans la ville de Québec sur la base de ses caractéristiques physiques et du profil des PMR. En conclusion, une approche visant le routage personnalisé pour les PMR a été développée.

En général, pour aider les personnes pendant leur mobilité, les technologies d'assistance ne sont pas conçues pour tenir compte des capacités personnelles et de la complexité de l'environnement. Les technologies d'assistance doivent fournir des informations, à la fois des variables dynamiques et statiques, sur les environnements complexes et prendre en compte les capacités des humains pendant leur mobilité. Les techniques d'assistance à la navigation permettent : 1) de guider une personne tout en tenant compte de ses capacités par rapport aux facteurs de l'environnement physique et 2) de suivre les changements dans l'environnement et ses environs tels que les humains et les objets intégrés à l'environnement.

De nombreuses technologies ont été développées pour aider les individus pendant leur mobilité ou créer un environnement interactif pour les guider pendant leur mobilité. En général, les technologies de guidage peuvent être portées par des individus (ex. les montres intelligentes) ou être placées à proximité (ex. les téléphones intelligents). Ces technologies d'assistance peuvent inclure des capteurs tels qu'un GPS, un accéléromètre, un magnétomètre, un gyroscope, une caméra intégrée dans le téléphone intelligent ou des capteurs intégrés dans des vêtements intelligents portés par des personnes. Cependant, certaines de ces techniques ont leurs propres limites en fonction du contexte de l'application et de la capacité de la personne qui les utilise. Par exemple, le GPS ne peut pas fonctionner dans l'environnement intérieur, en raison de l'atténuation de ces signaux (Fallah et al., 2013).

Pour pallier ces limitations, les réseaux de capteurs sans fil (RCSF) intégrés dans des environnements physiques permettent d'acquérir non seulement les informations dynamiques sur l'environnement, mais aussi de créer des environnements intelligents et interactifs qui peuvent aider efficacement les personnes dans leur mobilité. Les réseaux de caméras sont des exemples de ces technologies qui sont utilisées pour mesurer le volume de trafic en suivant les personnes et autres objets mobiles. Il faut noter que l'objectif de la stratégie du réseau de capteurs est d'observer les éléments d'une vue extérieure vers une vue intérieure, alors que les technologies d'assistance augmentées sur le corps humain sont en mesure d'observer les éléments de l'environnement d'une vue intérieure vers une vue extérieure.

L'un des principaux défis de placement d'un réseau de capteurs est de savoir où déployer les capteurs dans un environnement donné. L'emplacement de ces capteurs doit être effectué de manière optimale afin que les données pertinentes sur le dynamisme intérieur puissent être captées avec une couverture maximale toute en assurant le maintien d'une connexion minimale entre les nœuds du réseau (Akbarzadeh et al., 2013). La problématique de couverture maximale d'un réseau de capteurs a été au centre de nombreux travaux de recherche. Dans ces travaux, l'objectif principal était le déploiement optimal des réseaux de capteurs par des approches globales ou des approches locales (Argany et al., 2011). Dans ces approches, le type de capteurs et les caractéristiques de l'environnement ainsi que le type d'application peuvent compliquer le processus d'optimisation.

En conclusion, l'émergence des différents types de technologies de suivi, de surveillance, d'observation et de positionnement d'objets mobiles dans les environnements intérieurs complexes offre de nouvelles opportunités aux experts et aux chercheurs afin d'envisager le développement de technologies pour mieux aider les PMR lors de leur mobilité. De ce fait, dans ce projet de recherche doctorale, nous proposons des méthodes pour faciliter la conception et le développement des environnements interactifs et ambiants en utilisant une configuration de capteurs optimale pour améliorer les performances de mobilité des PMR. À cet égard, la position et le type de capteurs ont des impacts majeurs sur l'efficacité de la solution proposée.

1.2. Problématique

Les systèmes de navigation sont de plus en plus utilisés pour aider des personnes dans leur mobilité quotidienne. Cependant, comme indiqué précédemment, il existe plusieurs défis pour adapter et améliorer l'utilisation de ces systèmes pour mieux considérer les interactions entre les PMR et leur l'environnement qui nécessitent plus d'investigation. L'un de ces défis est la détermination des facteurs pour indiquer où ces interactions sont médiocres et doivent être améliorées. La lisibilité de l'environnement, en tant qu'indicateur efficace, doit être étudiée de manière approfondie pour identifier les zones plus complexes pour la mobilité des PMR. Cette étude présente non seulement un moyen d'améliorer les interactions entre les PMR et leur environnement, mais elle suggère également une stratégie pour améliorer l'utilisation d'un système de navigation pour les PMR en tirant du profit de l'avancement de la technologie d'un réseau de capteurs déployé de façon optimale dans l'environnement intérieur.

1.2.1. Problème général

Malgré l'avancement des systèmes de navigation, ces systèmes ne sont pas adaptés à l'usage des PMR en particulier dans l'environnement intérieur. Dans ce contexte, la création des environnements ambiants et interactifs présente une solution complémentaire pour mieux aider la mobilité des PMR. Cependant, les méthodes actuelles de déploiement d'un réseau de capteurs ne considèrent que les modèles simplifiés des capteurs de l'environnement intérieur. Elles ne sont généralement pas adaptées aux problématiques de guidage adapté des PMR pendant leur mobilité. En outre, les réseaux de capteurs en tant que solution ne sont pas bien conçus et optimisés pour améliorer les interactions des PMR à des fins de mobilité. Malgré le fait que les méthodes de déploiement de capteurs ont bien été étudiées, la majorité des recherches a considéré le modèle de captage simple des capteurs (circulaire ou sphérique dans le meilleur des cas) et de l'environnement 2D (sans obstacle) pour estimer la couverture spatiale du réseau. Cela limite notre capacité à concevoir des environnements ambiants adaptés à la mobilité des PMR.

1.2.2. Problèmes spécifiques

Compte tenu du problème général, les problèmes spécifiques de cette thèse sont exposés dans les sous-sections suivantes.

1.2.2.1. Absence de cadre conceptuel pour l'évaluation de la lisibilité de l'environnement intérieur pour les PMR

Comme mentionné précédemment, la lisibilité d'un environnement est un facteur clé qui influence les performances de mobilité des individus. La lisibilité dépend de la nature de l'interaction qu'ont ces individus avec leur environnement. Dans la littérature scientifique (Li & Klippel, 2016; O'Neill, 1991), plusieurs facteurs sont utilisés pour évaluer la lisibilité d'un environnement intérieur, dont le niveau de connectivité et la complexité de l'aménagement intérieur qui peuvent être mesurés à l'aide des indicateurs tels que la densité interconnectée (DIC) (Meilinger et al., 2012). Cependant, d'autres facteurs comme le niveau d'accessibilité de l'environnement et la présence de points de repère (en fonction de l'emplacement, de la couleur et de la taille) et d'éléments informatifs (par exemple, la signalisation à l'intérieur des bâtiments) peuvent influencer considérablement la lisibilité de l'environnement intérieur pour les PMR (Gharebaghi et al., 2017 et 2018; Sharma, 2015; Vazquez et al., 2010). Outre les facteurs environnementaux, la mobilité des PMR dépend également de facteurs personnels, y compris leurs capacités et leurs expériences. À notre connaissance, il existe très peu d'études qui prennent explicitement en compte les facteurs personnels lors de l'évaluation de la lisibilité d'un environnement pour les PAI (Belir & Onder, 2013; Vazquez et al., 2010). En particulier, la modélisation de la lisibilité des environnements intérieurs pour les PMR n'a pas été étudiée.

1.2.2.2. Limitations des méthodes d'optimisation pour le déploiement de capteurs dans un environnement intérieur 3D complexe

Les méthodes actuelles de déploiement de réseaux de capteurs sont pour la plupart expérimentales, rarement contextuelles et ne tiennent pas compte de la complexité de l'environnement. Elles utilisent généralement les modèles simplifiés de capteurs (champs de détection) ainsi que l'environnement dans lequel les capteurs sont placés. Cela est particulièrement vrai pour les environnements intérieurs et extérieurs construits où la présence des objets 3D, tels que les bâtiments, les murs, les arbres et les escaliers, complexifie non seulement la communication entre les capteurs, mais également leur placement et leur optimisation. Ces dernières années, des efforts ont été faits pour améliorer les modèles de capteurs et donc augmenter la qualité des mesures obtenues à partir d'un réseau de capteurs. Par exemple, dans Konda et al. (2016), le déploiement de caméras sans fil a été réalisé en considérant la qualité des images liées aux ressources lumineuses, les phénomènes de distorsion dans les caméras, la zone de couverture ainsi que la contrainte de connectivité entre les caméras dans des environnements intérieurs.

Cependant, les problèmes concernant le placement optimal des réseaux de capteurs dans un environnement intérieur persistent. En effet, les méthodes d'optimisation existantes pour le déploiement et l'optimisation des réseaux de capteurs ne prennent pas en compte la complexité de l'environnement en relation avec la diversité des obstacles, la complexité architecturale ainsi que la nécessité de gérer les caractéristiques 3D et leurs relations spatiales. De plus, la plupart des travaux de recherche ont optimisé la configuration des capteurs avec des méthodes stochastiques généralement très chronophages et peu efficaces. Au contraire, les méthodes d'optimisation locale utilisant la force virtuelle (Zou & Chakrabarty, 2003) et le diagramme de Voronoi (Wang et al., 2006, Argany et al., 2012) ont démontré une meilleure performance à cet égard. Les approches de force virtuelle ont un nombre élevé de paramètres, ce qui fait que l'algorithme reste dans les optima locaux, tandis que le diagramme de Voronoi est une méthode de partitionnement rapide avec prise en compte des informations de proximité avec les paramètres de réglage minimaux.

1.2.2.3. Manque de considération des besoins spécifiques en lien avec la mobilité des PMR et l'hétérogénéité de capteurs pour assurer le positionnement et le suivi des utilisateurs.

Différentes méthodes d'optimisation ont été proposées ces dernières années pour déployer les capteurs de suivi en tenant compte des caractéristiques de l'environnement. Ces méthodes sont souvent très génériques et elles ne sont généralement pas adaptées pour une application spécifique. Surtout dans le cas des capteurs de suivi, le seul but a été de choisir de surveiller l'ensemble de l'environnement, par exemple en augmentant la sécurité (Yaagoubi et al., 2015), alors que cet objectif n'a pas priorisé la zone couverte dans l'environnement. Jusqu'à présent, les méthodes d'optimisation du déploiement des capteurs n'ont pas été proposées pour déployer des capteurs de suivi dans le but d'assister les PMR dans leur tâche de mobilité. Bien que les capteurs pour faciliter la mobilité aient été séduits au cours des dernières décennies, l'approche de déploiement des capteurs a généralement été menée manuellement et par méthode d'essais et d'erreurs. Seules quelques études se sont concentrées sur l'objectif de mobilité, mais les éléments environnementaux et personnels n'ont pas été pris en compte ou ont été simplifiés.

De plus, l'hétérogénéité du type de capteurs au sein du réseau (réseau de capteurs multi-types) a été l'un des principaux défis du déploiement des réseaux de capteurs pour mieux répondre aux besoins exprimés dans le cadre d'une application telle que la mobilité des PMR. L'hétérogénéité des capteurs a été considérée dans le processus de leur déploiement selon des méthodes globales dans plusieurs recherches (Cao et al., 2018; Sušanj et al., 2020), tandis que très peu de recherches utilisent les algorithmes locaux en tenant compte des capteurs multi-types, car le processus de l'algorithme global est basé sur le calcul de l'estimation de la couverture des modèles de capteurs multi-types. Par exemple, dans les travaux de Tan et al. (2019), la structure Voronoi pondérée a été utilisée pour déployer des capteurs avec des champs de détection hétérogènes. Le déploiement de capteurs multi-types et leur optimisation (avec des champs de détection différents) posent des problèmes plus complexes, et peu de travaux abordent la complexité de l'optimisation de ces réseaux dans le contexte de la mobilité.

1.3. Objectifs de recherche

Les problèmes de déploiement des capteurs ont été étudiés dans de nombreux travaux de recherche. De nombreux efforts ont été faits pour répondre à ces problèmes, mais certains défis, concernant la complexité des capteurs, de l'environnement et de son application, nécessitent une investigation plus approfondie. Dans cette section, nous présentons l'objectif général ainsi que les objectifs spécifiques de cette thèse.

1.3.1. Objectif général

L'objectif général de cette thèse est d'améliorer le processus de déploiement des capteurs pour augmenter son efficacité pour guider les PMR lors de leur mobilité, soit de trouver l'emplacement optimal des capteurs en tenant compte non seulement des caractéristiques de l'environnement intérieur, des caractéristiques des capteurs utilisés, mais également des besoins spécifiques de mobilité des PMR (par exemple, la lisibilité). Par conséquent, explorer les défis des PMR dans leur mobilité, tel que le niveau de la lisibilité personnalisée de l'environnement, est un enjeu important en lien avec l'objectif général de la présente thèse. Un autre aspect de l'objectif principal de cette thèse est d'étudier la capacité des algorithmes d'optimisation afin d'introduire un algorithme pour déployer des capteurs en tenant compte de la complexité de l'environnement et de la mobilité des PMR.

1.3.2. Objectifs spécifiques

Afin d'atteindre l'objectif général de cette thèse, les objectifs spécifiques ont été définis comme suit :

1.3.2.1. Proposition d'un cadre conceptuel d'évaluation de la lisibilité de l'environnement intérieur pour les PMR

Le premier objectif de ce travail de recherche est de proposer un nouveau cadre conceptuel d'évaluation de la lisibilité pour les PMR. Ce cadre comprend les facteurs personnels et environnementaux de l'environnement intérieur. La lisibilité est considérée comme le résultat de l'interaction entre les facteurs personnels et environnementaux en fonction de la capacité et de l'expérience des personnes. Les principaux facteurs physiques (par exemple, la visibilité) qui affectent les personnes à la compréhension de leur environnement servent de facteurs influents à l'évaluation de la lisibilité. La prise en compte de la méthode appropriée pour évaluer les interactions entre les facteurs personnels et les facteurs environnementaux (ex. pentes, rampes, marches, etc.) est une partie importante de cet objectif de recherche.

1.3.2.2. Proposition d'un algorithme d'optimisation locale basé sur la structure Voronoi 3D pour le déploiement de capteurs dans l'environnement intérieur 3D,

Proposer un algorithme d'optimisation locale pour le déploiement des capteurs dans l'environnement intérieur 3D est un autre objectif spécifique de cette thèse pour aborder la complexité de la structure de l'environnement intérieur (par exemple, la hauteur de divers plafonds) afin de maximiser la couverture des capteurs. Afin de développer cet algorithme, les interactions entre les éléments environnementaux et les capteurs sont considérées pour améliorer la couverture du réseau. Par conséquent, un modèle de représentation de l'environnement intérieur (par exemple, l'IndoorGML) doit être appliqué pour considérer les interactions entre les éléments environnementaux. Ensuite, le modèle Voronoi 3D créé à partir des positions des capteurs peut être utilisé pour considérer les interactions des capteurs. Ces deux modèles doivent être intégrés dans l'algorithme d'optimisation pour améliorer la couverture du réseau de capteurs dans l'environnement intérieur. Ainsi, la stratégie de mouvement des capteurs nécessaire pour le processus d'optimisation du réseau de capteur doit être définie en tenant compte des informations issues de l'IndoorGML et du diagramme Voronoi 3D.

1.3.2.3. Développement d'un algorithme d'optimisation adapté pour le déploiement de capteurs multi-types dans l'environnement intérieur pour aider la mobilité des PMR

Le déploiement optimal du réseau de capteurs multi-types avec prise en compte de la lisibilité des PMR de l'environnement dans leur mobilité selon le cadre proposé pour une lisibilité personnalisée est le troisième objectif de cette thèse. Les différents types de capteurs avec leurs paramètres doivent être modélisés pour être déployés dans l'environnement intérieur à cet effet. En plus des modèles environnementaux et des capteurs, la lisibilité doit être intégrée par rapport aux besoins des PMR dans l'estimation de la couverture. De plus, l'estimation probabiliste de la couverture des capteurs est considérée pour obtenir un déploiement plus réaliste.

1.4. Méthodologie

La méthodologie a été organisée en quatre phases pour atteindre les objectifs de la thèse. Les différentes phases ont été définies afin d'atteindre des objectifs de la thèse.

1.4.1. Phase 1 : Réaliser une revue de la littérature

La première phase de notre méthode consistait à passer en revue la littérature pertinente sur les questions connexes, notamment l'environnement intérieur, la mobilité des PMR, les technologies d'assistance et les algorithmes d'optimisation du déploiement des RCSF. Cette phase nous a permis d'identifier les problèmes à résoudre, de définir les objectifs du projet et également de déterminer les méthodologies appropriées pour nos recherches. De plus, cette phase a fourni les fondements théoriques de cette recherche.

1.4.2. Phase 2 : Définir un nouveau cadre pour l'évaluation de la lisibilité personnalisée des PMR de l'environnement intérieur

Dans cette phase, nous avons défini un nouveau cadre conceptuel pour définir et évaluer le concept de la lisibilité de l’environnement intérieur par les PMR inspiré du modèle du PPH (Fougeyrollas et al., 2019). La lisibilité d'un environnement est un indicateur qui mesure le niveau de complexité et la facilité de compréhension de cet environnement par une personne. Compte tenu des facteurs environnementaux dans le calcul de la lisibilité, tels que la connectivité entre les corridors et les notions de facilitateurs et d'obstacles, un nouveau cadre a été créé pour personnaliser l'évaluation de la lisibilité pour les PMR. Dans cette évaluation, certaines des perceptions et interactions des PMR avec les éléments environnementaux au cours de leur mobilité se produisent de différentes manières et conduisent par conséquent à différentes cartes mentales, de sorte que ces personnes perçoivent et interagissent différemment avec des objets tels que les ascenseurs, les escaliers mécaniques et les marches pendant leur mobilité, puis leurs perceptions de la lisibilité de l'environnement peuvent être différentes. En effet, nous avons intégré l'influence des obstacles et des facilitateurs aux facteurs déjà considérés dans le processus d'évaluation de la lisibilité.

Pour effectuer le calcul de lisibilité pour les PMR à partir de l'environnement intérieur, le modèle 3D d'un environnement intérieur complexe a été créé par un scanneur de nuage de points 3D et la vidéo géolocalisée a été collectée pour obtenir la saillance visuelle de l'environnement en tant que facteur qui influence la lisibilité des personnes. Ensuite, les actions suivantes ont été effectuées pour agréger différents facteurs afin de calculer la lisibilité pour une personne utilisatrice d’un fauteuil roulant manuel en tenant compte de son niveau de confiance vis-à-vis divers obstacles / facilitateurs qu'elle pourrait avoir rencontrés lors de ses expériences passées.

1.4.3. Phase 3 : Développer un nouvel algorithme d'optimisation locale pour le déploiement des capteurs dans l'environnement intérieur complexe 3D

Dans cette phase, une approche d'optimisation utilisant les interactions entre les éléments environnementaux et les capteurs a été modélisée pour concevoir un réseau de capteurs optimal. Cette approche a utilisé les informations contenues dans le modèle IndoorGML de l'environnement intérieur défini par le Consortium géospatial ouvert (CGO) et la structure Voronoi 3D créée par la configuration des capteurs. La structure principale d'IndoorGML divise l'espace intérieur en plusieurs espaces, appelés cellules (par exemple, pièces et couloirs), et la zone d'intersection de deux cellules voisines est appelée surface frontière (Li et al., 2019). Le diagramme de Voronoi 3D est utilisé pour la représentation des capteurs et leurs relations de proximité dans des espaces intérieurs 3D. Notre nouvel algorithme d'optimisation locale pour le déploiement des capteurs a bénéficié de ce modèle intégré pour la maximisation de la couverture du réseau de capteurs. Afin de calculer la couverture d'un réseau de capteurs, la position et la couverture individuelles des capteurs ont été déterminées à l'aide des informations fournies par le modèle IndoorGML. Dans cette phase, la surface du plancher de chaque cellule était considérée comme étant la surface cible à couvrir par les capteurs. En fonction des positions des capteurs dans la structure de Voronoi et compte tenu de la présence de divers obstacles dans l'environnement, l'estimation de la couverture a été calculée.

Dans l'approche d'optimisation, un algorithme itératif a été développé pour maximiser la couverture du réseau de capteurs. À chaque itération, un capteur individuel est déplacé vers sa nouvelle position qui permet d'améliorer la couverture totale du réseau de capteurs. Ce mouvement est basé sur des informations contextuelles et est sensible à la forme et à la présence d'obstacles dans l'environnement ainsi qu'à la présence d'autres capteurs à proximité du capteur à évaluer. En tant que stratégie de mouvement, chaque capteur est déplacé vers le sommet le plus éloigné de sa cellule Voronoi 3D en ajoutant une force de répulsion des barrières pour éloigner les capteurs des obstacles et garder leur place sur les murs ou les plafonds par la projection du vecteur de mouvement sur la surface la plus proche du capteur (murs ou plafonds). Le vecteur de mouvement projeté et la couverture de la configuration des nouveaux capteurs sont ajoutés dans une liste de priorités qui permet à l'algorithme de choisir la meilleure configuration de capteurs à chaque itération.

1.4.4. Phase 4 : Proposer un nouvel algorithme d'optimisation pour le déploiement de capteurs multi-types dans un environnement intérieur complexe 3D pour faciliter la mobilité des PMR

Dans cette phase, le déploiement des capteurs fait référence aux interactions entre les capteurs eux-mêmes avec les éléments environnementaux environnants et au cadre d'évaluation de la lisibilité en fonction des résultats des interactions entre une personne à mobilité réduite et son environnement en fonction de la tâche de mobilité, qui ont été intégrés pour développer un nouvel algorithme d'optimisation ciblée. Pour fournir un processus interactif intelligent dans le déploiement des capteurs pour faciliter la mobilité des PMR, nous avons exploité les interactions entre : 1) les éléments de l'environnement à l'intérieur de la structure IndoorGML (couche IndoorGML), 2) les capteurs avec la structure Voronoi 3D et 3) les PMR avec l'environnement pour effectuer la tâche de mobilité avec la couche de lisibilité.

Afin d'intégrer l'information de la lisibilité des PMR avec l'information issue des modèles IndoorGML et Voronoi 3D pour l'optimisation des capteurs, une nouvelle stratégie d'estimation de couverture pondérée et de mouvement des capteurs a été définie. L'estimation de la couverture pondérée a été définie non seulement via les facteurs environnementaux et les caractéristiques des capteurs, mais aussi l'approche de pondération a été désignée dans l'estimation de la couverture basée sur la couche de lisibilité. De plus, dans le processus d'optimisation, la stratégie de mouvement des capteurs a été définie permettant le mouvement itératif des capteurs vers leur sommet le plus éloigné de la cellule Voronoi respectif, ainsi que la valeur de lisibilité la plus basse dans sa cellule en tenant compte des éléments environnementaux (obstacles) et l'information sur la zone déployable (murs et plafonds) stockée dans le modèle IndoorGML. Pour prendre en compte la diversité des types de capteurs utilisés (ici, les champs de détection différents de Bluetooth et Camera), la taille de pas dans la stratégie du mouvement des capteurs est définie en fonction du rapport entre le champ de détection du capteur et le champ de détection maximale dans le réseau.

Pour la fin de la validation de l'algorithme proposé dans le cadre d'une étude de cas, nous avons défini le modèle des caméras et des capteurs Bluetooth en fonction des caractéristiques de leurs capteurs, telles que leur fonctionnalité de visibilité et leur champ de détection. Nous avons considéré le modèle de caméra comme un capteur omnidirectionnel et défini sa couverture en fonction de la probabilité de son champ de détection. Le modèle de probabilité de visibilité du capteur Bluetooth a été considéré en fonction du signal (dB) reçu de l'émetteur (par exemple, le téléphone personnel) qui est diminué de façon logarithmique en augmentant la distance entre le capteur et la cible ainsi que la présence d'un obstacle comme un mur avec une épaisseur. En plus des modèles de capteurs, le modèle d'environnement 3D et la couche de lisibilité obtenue en phase 2 ont été pris en compte dans les expérimentations.

L'approche méthodologique de cette thèse est illustrée à la Figure 1.1.

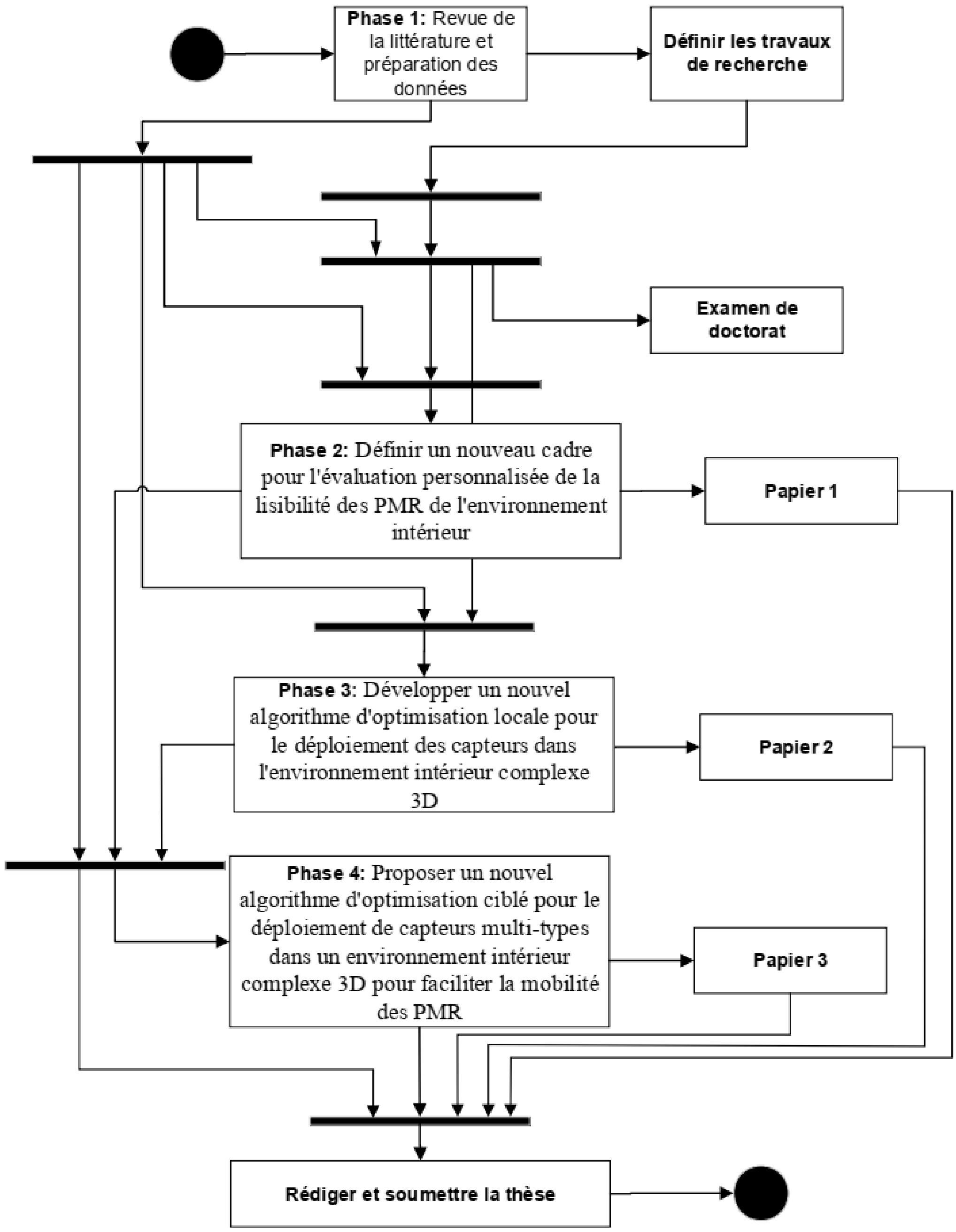

Figure 1.1: Le schéma de la méthode de recherche

1.5. Organisation de la thèse

Cette thèse est rédigée sous forme d'articles. Elle est composée de six chapitres. Le premier chapitre porte sur la définition du contexte de recherche et il présente les problèmes, les objectifs généraux et spécifiques de la thèse ainsi que la méthode de recherche.

Le deuxième chapitre présente un aperçu de la recherche sur les problèmes de mobilité et de navigation spécifiquement pour les PMR, un examen de la façon dont l'intégration des technologies de capteurs sans fil peut améliorer la mobilité des PMR et l'identification des défis pour le déploiement optimal d'un réseau de capteurs.

Le troisième chapitre présente un nouveau cadre conceptuel d'évaluation de la lisibilité personnalisée des PMR de l'environnement intérieur, inspiré du modèle PPH et créé sur la base de l'intégration de facteurs personnels et environnementaux. Ce chapitre fait l'objet du premier article publié dans la revue scientifique « *l'International Journal of Geo-Information (IJGI)* » en 2020.

Le quatrième chapitre est un article qui présente un nouvel algorithme d'optimisation locale pour le déploiement de capteurs dans un environnement intérieur complexe 3D par intégration de la tessellation Voronoi 3D d'un réseau de capteurs et d'un modèle IndoorGML en tant que modèle géométrique et topologique de l'environnement intérieur. Ce chapitre a été publié dans la revue scientifique « *Sensors Journal* » en 2021.

Le cinquième chapitre qui est également écrit sous forme d'un article porte sur le développement d'un algorithme d'optimisation orienté vers l'objectif pour le déploiement de capteurs multi-types dans l'environnement intérieur pour aider à la mobilité des PMR. Il propose une nouvelle optimisation locale basée sur le diagramme de Voronoi 3D, IndoorGML et la couche de lisibilité pour les PMR afin d'explorer où sont les positions optimales des capteurs pour aider à améliorer la mobilité des PMR et résoudre le défi du déploiement de capteurs multi-types par une approche d'optimisation locale. Ce chapitre a été soumis à la revue « *Geo-Spatial Information Science* » en 2022.

Le dernier chapitre présente les conclusions et les perspectives de cette recherche.

Les articles de cette thèse proviennent d'un même projet de recherche. Par conséquent, le contenu de la thèse peut sembler redondant dans certains chapitres. Cependant, cela était nécessaire afin de garantir que chaque article est complet et que le lecteur a suffisamment des détails pour comprendre la contribution originale présentée dans l'article sans être obligé de lire l'ensemble de la thèse.

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2. Vue d’ensemble de la mobilité et du déploiement des réseaux de capteurs

2.1. Résumé

La mobilité et la participation sociale des PMR peuvent être limitées en présence de différents facteurs environnementaux (par exemple, monter des escaliers et des marches). En effet, selon le modèle de développement humain, le niveau de participation sociale de PMR dépend fortement de la qualité de l’interaction de la personne avec son environnement. Les éléments environnementaux peuvent soit créer des difficultés en tant qu'obstacles (par exemple, des escaliers), soit faciliter la tâche de mobilité en tant que facilitateurs (par exemple, une signalisation). En particulier, le modèle du processus de production du handicap (PPH) fournit la base nécessaire pour la conception inclusive des environnements et sans obstacle pour favoriser la participation sociale des PMR. Dans ce contexte, l’intégration de nouvelles technologies dans l’environnement permet de venir en aide à la mobilité de ces personnes dans leurs environnements intérieurs. L'une des technologies d'assistance consiste à améliorer l'environnement en utilisant des capteurs pour faciliter les interactions entre les PMR et l'environnement. Une solution efficace est le déploiement d'un réseau de capteurs optimal afin de mieux localiser et suivre la dynamique des PMR pour aider les PMR dans leur mobilité. Ce chapitre présente un aperçu des enjeux de mobilité et de navigation des PAI dans des environnements intérieurs avec un accent spécifique sur la mobilité des PMR. Il présente également une revue de littérature sur la dynamique de l'environnement et l'importance des capteurs dans le suivi et observation de ce dynamisme en lien avec la mobilité. De plus, une discussion des problèmes de déploiement de capteurs et des facteurs contributifs concernant la configuration optimale des réseaux de capteurs, tels que l'estimation de la couverture du réseau, les modèles de capteurs et les approches d'optimisation pour le déploiement des capteurs, est amorcée. Enfin, les approches existantes de déploiement de capteurs dans le but d'application de mobilité seront discutées.

An overview of mobility in presence of a sensor network

2.2. Context

Over the past decades, there has been an important progress in sensor network technologies in terms of higher precision, lower cost, and smaller size to monitor different dynamic phenomena in the environment (Argany et al., 2011). There is a wide set of applications for sensor networks ranging from security to traffic, human activity, industrial fields, health care applications (e.g. virus contagion), etc. (Bertinato et al., 2008). One of the main challenges in the design of sensor networks is how they can be deployed optimally in the environment. The optimal deployment means that the dynamic phenomena can be efficiently monitored with the maximum coverage of the whole area as well as the maintenance of the minimum connections between the network nodes (Huang et al., 2014) at minimum cost. Sensor deployment optimization algorithms with the aim of maximum coverage are categorized into global and local algorithms. Sensor types and the presence of obstacles in the environment can complicate the optimization process and lead to poor results in achieving local optima (Argany et al., 2018).

Although several optimization algorithms have been proposed to deploy the sensors while taking into consideration the environmental elements which may hinder the sensor's visibility (Argany et al., 2018), they have not been usually designed for a specific purpose such as the mobility of PWMD. Mobility and the social participation of PWD may be constrained by the presence of environmental factors (e.g., encountering stairs, or steps). These limitations result from poor interactions between these people with their environment (Gharebaghi et al., 2018). The environmental factors can either be qualified as obstacles (e.g., stairs) or facilitators (e.g., signage). In particular, the disability creation process (DCP) model provides a better model for assistive technologies by considering the result of interactions between environmental and personal factors to better meet the needs of PWMD (Fougeyrollas et al., 2019). One of these assistive technologies is the deployment of the sensor networks in the environment to support PWMD during their mobility. In particular, an efficient solution for the mobility of PWMD in an indoor environment is the deployment of an optimal sensor network in order to better track, monitor and provide them with useful information where they need it most.

Hence, this chapter presents an overview of the mobility and navigation issues in an indoor environment with a special focus on the mobility of PWMD (Sections 2.2 and 2.3). It also provides a survey of the sensor networks and their importance for the observation and monitoring of the dynamics of the environment (Section 2.4). Next, sensor deployment issues and contributing factors concerning the optimal configuration of the sensor networks such as network coverage estimation, sensors models, and the optimization approaches for the sensor deployment will be presented. Finally, the limitations of the existing approaches for optimal sensor network deployment will be discussed.

2.3. Mobility

Mobility is one of the most important life habits for humans. Mobility contributes to the achievements of other life habits such as nutrition, traveling, and entertainment (Fougeyrollas et al., 1998). Obstacles and facilitators may limit or facilitate the mobility of people in different ways. The environment may be classified from different points of view and may include indoor and outdoor environments that are physical or social, or static or dynamic (Gharebaghi & Mostafavi, 2016). In the outdoor environment, mobility is carried out in the pedestrian or vehicular road networks, whereas in indoor environments, corridors, elevators, and stairs are used for mobility and navigation purposes. The complexity and dynamics of these structures result in more complex navigation. This is especially more challenging when the special needs of PWMD are considered for their mobility and navigation. For example, the mobility of a person who uses a manual wheelchair becomes more complex compared to that of the general population. The built environment is generally conceived based on a standard view of people without disabilities and the capacities and the special needs of PWMD are rarely considered (Gharebaghi et al., 2017). To overcome these complexities and limitations, the environment should be adapted to the needs of these individuals and a more universal approach to designing and developing urban indoor and outdoor environments must be considered.

In addition to the environmental factors, personal factors play an important role in carrying out the mobility task. Personal factors include elements such as capabilities, identity, preferences, and human organic systems (Fougeyrollas et al., 1998). Cognition, the mechanical act, sensory organs, confidence, and perception are the elements which determine the capability of the human. Personal factors such as age, sex, and education are among the factors that also influence the mobility task.

Other factors that influence mobility task are related to the objective of the mobility (Alfonzo, 2005). The preferences of humans have impacts on their mobility behaviour to accomplish diverse daily activities. For example, in a museum, a person may prefer to walk along the aisles occupied with historical relics regardless of the extra time that may take, but in a shopping mall, a person may need to find the shortest way for getting the expected products. As a general view, in addition to the consideration of these factors separately, their interaction, either implicitly or explicitly, may also impact the final mobility of an individual.

Accordingly, the complexity of interactions between personal and environmental factors and the objective of mobility may limit or even make the mobility task impossible for a person. To overcome these challenges, several assistive technologies and navigation systems have been developed to facilitate individuals' mobility during recent years (Harris et al., 2005; Mostafavi, 2015). Recent advances in geospatial and communication technologies (e.g., smartphones, navigation, positioning technologies, sensor networks, Internet of Things, etc.) (Carver et al., 2016; Fallah et al., 2013; Kohoutek et al., 2010; Mnasri et al., 2018) allow us to design and develop more adapted and inclusive environments to facilitate the mobility of PWMD by guiding them to their destination and providing them pertinent information such as obstacles and facilitators on their path. The design and development of such inclusive environments necessitate the consideration of knowledge of the perception, capabilities, experiences, and preferences of these people in their mobility and interactions with the environment.

The legibility of an environment is another key factor that influences mobility performance. It contributes to the construction of a cognitive map, that is, a mental map of the environment which is used for navigation tasks. In the next subsection, the legibility concept will be elaborated and positioned in relation to the mobility of PWMD.

2.3.1. Legibility

The legibility of the environment provides a link between human perceptions and the physical environment that influences the performance of wayfinding behavior. In general, the legibility of an indoor or outdoor environment is defined as "*the ease with which its parts can be organized into a coherent pattern*" (Lynch, 1960). Lynch (1960) conducted a study of environmental legibility in support of wayfinding. He showed how distinct landmarks can affect the legibility of a city. His idea was introduced as the amount of suppleness that is necessary to recognize a coherent pattern from the surrounding environment. O'Neill (1991) proposed a conceptual model for legibility that introduced a cognitive map as an intermediary between the designed physical environment and wayfinding performance. A cognitive map is understood to be the mental representation of the environment that serves to indicate spatial and topological relations between connected places.

Several legibility and complexity analyses of physical environments have also been reported in recent years in support of wayfinding applications. In general, the legibility factors addressed included: (1) visual access, (2) the level of connectivity, and (3) the level of complexity of the environmental layout. Low environmental visibility makes it more difficult to find the location of a destination. Benedikt (1979) used the isovist method for assessing the visual access of an environment. The level of connectivity is the degree of integration between convex spaces. An axial map can be applied to measure the pattern of line-of-sight connections between spaces (Siegel & White, 1975). Finally, the level of complexity is usually calculated based on the InterConnected Density (ICD), that is, a measure of the amount of complexity of a planar network structure. In fact, ICD represents the average degree of connectivity for each node over the whole network. Li and Klippel (2016) have applied these factors to suggest where the environment is more understandable. They integrated these factors into a definition of legibility.

Like legibility, the level of accessibility of an environment may impede the mobility behavior of people using wheelchairs or, alternatively, may facilitate their movement, in particular, within the buildings. Accessibility is the degree to which an object can be reached or approached (Welage & Liu, 2011). According to the Americans with Disabilities Act Accessibility Guidelines (ADAAG) (Leonard, 2000), for accessibility analysis, indoor spaces are classified into: (1) primary path segments, (2) secondary path segments, (3) closed space-like rooms, (4) open space-like corridors, (5) doors, (6) stairways, (7) elevators, (8) ramps, and (9) furniture. Most recently, Yaagoubi et al. (2020) proposed a new method based on the Voronoi data structure to obtain a navigational network for PWMD using ADAAG classes and IndoorGML standards (Li et al., 2019). Additionally, Park et al. (2020) similarly investigated the accessibility of the navigational networks of two shopping malls. According to the American Disabilities Act (ADA) and the Barrier-Free Certification System (BFCS), they classified indoor spaces and their accessibility attributes into: (1) corridors (area, width, slope, and level change attributes), (2) elevators (area, passing width, and control buttons), (3) escalators (with ramps), (4) stairways (with wheelchair lift and ramp), (5) ramps (width, slope, turning width, and handrails), and (6) doorways (directions including push and pull, the existence of automated functions, width, height, and sill-like flats).

In order to efficiently guide a person through an indoor environment using a navigation system, we need information on the position of the people as well as information on the environment such as the configuration of rooms, corridors, stairs and elevators. Besides this, measuring the mobile objects' positions (e.g., people in motion) that may impinge on the mobility is also important. This information can be provided by a sensor network deployed inside the environment. Furthermore, the information of a user's position with respect to the environment is another significant information for guiding people and providing them with relevant information. In the following section, we briefly present navigation systems and their functionalities.

2.4. Indoor Navigation Systems

As smart assistive tools, indoor navigation systems offer several functionalities including positioning of a person with respect to the environment, planning an optimal route between two locations, representing the route, and providing functionalities for multimodal real time interactions between the user and the system (Fallah et al., 2013). The system feedback is provided using different visual, audial, and haptic modes. The aim of most navigation systems so far has been the implementation of these tasks by considering the information of the environment and rarely the user profile.

As an example of such navigation systems, the Wifaver application (Wecker et al., 2015) is designed for a museum service that uses a venue's Wi-Fi for positioning and a pre-planned path for guiding users through the museum. In other applications such as the SFO (San Francisco) airport (Airport, 2014), iBeacons (Bluetooth produced by Apple Company) are used for positioning. This application is specifically designed for blind and visually impaired persons. Cartogram (Cartogram, 2013) is another navigation application that uses Bluetooth beacons for displaying consumer products rapidly to customers. The Infsoft application (Infsoft, 2005) also uses a variety of sensors for positioning and other purposes such as GSM, 3G/4G (LTE), Wi-Fi, magnetic fields, compass, air pressure, barometer, accelerometer, gyroscope, Bluetooth, and GPS. Mathis and Kallstrom (2015) designed an indoor navigation system for the elderly people, which uses Bluetooth beacons for positioning. The Drishti system (Ran et al., 2004) for blind individuals is another system that considers several wearable components such as ultrasound tags, small computers, and headsets to inform the use of the presence of obstacles in the surrounding environment.

These navigation systems have been designed for mobile applications with considering the sensors on smart phones and rarely deployed in the environment. In addition, there is no adaptability between the environmental features and the personal profile for the majority of these applications. Apart from this, the main components of these navigation systems, the type of sensors, their locations, path planning method, and interactions between user and the system have not taken into consideration the needs of people nor their degree of satisfaction.

2.5. Dynamic indoor environments and their tracking with sensor networks

Urban environments are characterized by their static and dynamic dimensions (Fougeyrollas et al., 2019). The static dimension describes the parts of the environment that do not change over time, whereas the dynamic dimension includes any change occurring in the environment. In the mobility task for pedestrians, the static dimensions are mainly related to the static aspects of the pedestrian network such as width, length of a route segments, its pavement type, static obstacles such as furniture or stairs for people with motor disability, and point of interest. On the other hand, the dynamic dimension of the environment may include the presence of people or temporary construction work on the pedestrian network. In addition to the environment dynamics, personal factors also change with time and hence impact the mobility of people in the environment. For instance, people get older and their capabilities and skills evolves with time (Gharebaghi & Mostafavi, 2016).

Following are some examples of dynamic situations where monitoring and tracking of the environment would be essential to better help and guide people, in particular PWD, in an indoor environment and the situations where we need updated information on the trajectory.

- Tracking moving objects in an indoor environment: Moving objects can obstruct the path, and decrease the accessibility of the segments. For instance, in a crowded airport, people’s motions can create a barrier to impinge on the mobility of a PWMD (Gharebaghi & Mostafavi, 2016).

- Tracking people in an emergency situation (e.g. evacuation) to guide people to the exits from any point in the building via public ways with the lowest vulnerability (Zhang et al. 2019).

- Preventing possible collisions: Sensor networks can be used to track both a visually impaired person and other objects in the indoor environment to prevent possible collisions (Kayukawa et al., 2019).

- It can be possible to model people's movement in the indoor environment, and predict the travel time of the user during specific times during the day. For example, this can be important for vertical segments such as elevators (Silva et al., 2019).

- Other than navigation, the activities and behavior of people can be modelled based on tracking their information (proximity, trajectories clustering analysis, etc.) (Wang et al., 2017).

- Moreover, tracking people in motion can be useful to better manage location-based services, and optimally distribute the resources in the indoor environment (Yu et al., 2017).

- Last but not least, by tracking whether particular spots are occupied or not, the system can offer the vacant spot to the user. For instance, the chairs inside a conference room, or festival area, and parking slots can be tracked for better informing the users of what is available (Wu & Yeh, 2019).

In order to detect the dynamics of the environment for the mobility context such as identifying the potential obstacles that may occur in a navigable area (e.g., corridors), the environment can be equipped with sensor networks such as cameras, motion detection sensors, etc.

In recent years, various sensors have been developed and used for monitoring and measuring different dynamic phenomena in the environment. Sensors can measure either the characteristics of a particular spot or a limited area in the environment. The first type of sensor is called point-based, and the second type is called range-based (Guvensan & Yavuz, 2011). Point-based sensors include those that are used for the detection and measurement of phenomena such as light, temperature, humidity, and pressure. Range-based sensors such as cameras and Kinects use range sensing to measure the characteristics of a phenomenon in the surrounding environment. Indeed, the range-based sensors act similar to the point-based sensors measuring the dynamic elements near their positions, however, the difference is that these measurements can indicate the original cause of these dynamic elements. For instance, the detection of electromagnetic waves at one point can give us the information about the broadcasting origin of the wave.

For navigation and mobility purposes, the majority of sensors have been used for positioning tasks, which are generally embedded in smart phones or in wearable technologies. On the other hand, tracking sensors are generally embedded in the environment to monitor and detect dynamics. The embedded tracking sensors can constitute a multi-sensor network for the observation of the mobility-related activities. Embedded tracking sensors must be deployed in the environment in the best configuration to maximize the coverage and guarantee a minimum connectivity between sensor nodes in a network as well as to minimize the cost by considering the number and type of the sensors. The characteristics of sensors such as observation angles, distance ranges, data type, line of sight sensitivity, and the field of view impact the coverage of a sensor for detection of the dynamics of the environment. On the other hand, the static aspect of the environment including its configuration has an important impact on the optimal coverage of the environment to provide an efficient navigation for the PWMD.

2.6. Sensor Network Deployment Issues

Embedding a sensor network in an indoor environment for mobility is a challenging task. The inclusion of multiple sensors to equip the indoor environment for the navigation task constitutes a network of sensors. One of the important issues related to sensor networks is their optimal deployment in the environment. For sensor network deployment, there are issues related to the maximization of the network coverage and minimization of the network cost and battery consumption for each node as well as the need to maintain a minimum connectivity between nodes in wireless sensor network (WSN) (Akbarzadeh et al., 2011). Efficient sensor network deployment needs to be context-aware that considers the local information concerning the surrounding environment (e.g., obstacles), sensor parameters (e.g., range distance), as well as the context that the sensor network is used (Argany, 2015).

Sensor networks generally have two main application scenarios: tracking and monitoring. In both cases, it is essential that the target or environment information be detected and the data collected by the sensors (Iliodromitis & Lambrou, 2018). To achieve proper coverage, sensors are usually densely positioned. In addition, the lifespan of the sensor network is determined by the energy stored in the sensor nodes. To achieve longer network life, more energy must be allocated to the sensors. Because the sensors are equipped with limited and expensive batteries, locating a greater number of sensor nodes is an expensive process for the network energy maintenance. Therefore, in order to meet this goal in a network, the network sensing and communication performances must be evaluated numerically before its placement. Sensor network analysis such as network coverage, network connection, power consumption, and cost have been studied in several papers (Akbarzadeh, 2016; Ghosh & Das, 2006; Wang et al., 2006). Cheng et al. (2008) proposed a general framework for analyzing network longevity and cost for different placement strategies of wireless sensor networks. The issue of coverage in sensor networks has also been extensively investigated (Bai et al., 2008; Poe & Schmitt, 2009; Zhang & Hou, 2005). Zhang and Hou (2005) studied the difficulty of reaching the necessary density of sensor nodes to maintain a minimum k coverage. She et al. (2011) described analytical methods for modeling coverage when events are occurring dynamically (i.e., the network coverage needs to be maximized for detecting the whole event such as in the case of wildfires). Poe and Schmitt (2009) examined coverage, power consumption, and messaging performance among the sensor nodes for the large-scale wireless sensor networks.

Depending on the environment access for sensor network deployment, the sensors can be randomly or deterministically placed. For instance, when a volcano needs to be monitored by sensor networks, sensor nodes are dropped and placed randomly in the study area (Werner-Allen et al., 2006). However, in applications such as the monitoring of bridges or the building of structures, the sensors must be accurately positioned based on a regular pattern (Paek et al., 2005).

In general, there are several factors that contribute to a successful deployment of large-scale sensor networks (Akyildiz et al., 2002; Chong & Kumar, 2003; Tubaishat & Madria, 2003):

1. **Failure threshold:** Due to the accidental placement of sensors in harsh environments, some sensor nodes fail or disappear. Failure of a small number of sensors in the network should not affect the performance of the sensor network.
2. **Production cost:** Since a large number of microsensors are located in the network, it is vital that each microsensor have a very low cost to minimize the cost of the entire network. Some studies have suggested that the cost of micro-sensors should be affordable (Akyildiz et al., 2002). To reduce this cost, low-cost computers must either be used, or design algorithms for the operation of microsensor nodes must be upgraded.
3. **Hardware constraints:** A sensor node includes a tracking tool, a data processing tool, and a communication tool. In addition, depending on the application, it can include power generation tools, positioning tools, and mobility tools. Unlike older sensors, sensors must be able to organize themselves in the network. As a result, such capabilities complicate the design of hardware in terms of computational power. Indeed, the computational power of each sensor must be limited. Combining all tools with the least power consumption is one of the more important factors in network design (Tubaishat & Madria, 2003).
4. **Hard environment:** Sensors must be able to adapt to challenging or critical areas. They must also work well in areas that are not accessible. Examples of applications that depend on this include military applications and volcanic monitoring.
5. **Transmission:** Communication lines in wireless sensor networks can be radio, infrared or optical. In the latter two cases, the line of sight between the sender and receiver must be considered. Radio communication lines can be used to establish a global network connection. Most wireless sensor networks are based on radio communication.

6. **Energy Consumption:** Sensor nodes usually have batteries and their energy is limited. In many applications, such as for military, it is impossible to charge the batteries. The lifespan of micro-sensor nodes is highly dependent on the lifespan of their batteries. The lifespan of these nodes affects the lifespan of the network. Therefore, it is very important to consider algorithms that minimize grid energy consumption.
7. **Network coverage:** Sensor nodes should be located in areas that can collect the most significant information from the environment. Increasing the number of sensors and their operating range increases the network coverage and achieved better performance. However, it also increases power consumption and the cost of the network. For this reason, a balance must be struck between network coverage and energy consumption, and cost must be factored in as well. The purpose of this dissertation is to consider network coverage in the design of sensor networks.

2.6.1. Coverage problem in sensor networks

The coverage problem is subdivided into target- and area-based coverage problems. In some sensor network applications, detecting target points such as building, doors, flags, and boxes is desired, while in others the aim is the detection of mobile target points like intruders (Guvensan & Yavuz, 2011). Covering the target points, instead of the whole area, is the concern of the target-based coverage problem, whose purpose is to locate the maximum number of target points. In target-based coverage, any target must be covered by a sensor (Kumar et al., 2004). A main issue here is the presence of obstacles, which has not been considered in most current studies (Li et al., 2003). An exception is the effort to consider obstacles in target-based coverage developed to compute the best coverage path between two points in 2D environments (Roy et al., 2007), where the visibility graph (Welzl, 1985), a standard structure, has been used for evaluating the inter-visibility between the sensors and targets.

Another definition of coverage area was presented by Ahmad (2016). This research mainly focused on area-based coverage with a team of mobile robotic sensors and used the decentralized control strategy inspired by animal aggregation. The aim of this research was to place robotic sensors without drawing upon any global information about the network and the environment. In this research, coverage area was categorized into: (1) *blanket coverage*: using the triangular lattice pattern of sensors to cover the whole area, (2) *barrier coverage*: placement of sensors around landmarks for security reasons, (3) *sweep coverage*: movement of sensors to monitor the whole area as coverage sweeps across a line, (4) *heuristic coverage*: placement of robotic sensors to minimize coverage time, (5) *dynamic coverage (search and rescue)*: the sensors dynamically search the environment to cover a part of region for a specific period of time, (6) *3D coverage*: placement of sensors to cover the 3-dimensional space (e.g., coverage by Unmanned Autonomous Vehicle (UAV) robots in outdoor environments and three-dimensional ocean coverage of underwater acoustic sensor networks), and (7) *mobile* *actuator and sensor network coverage*: robots that act as actuators or as sensors may be deployed based on their tasks to achieve optimal performance. The limitation of this research was that the consideration of the environment was not included to determine the coverage for the robots. For instance, the 3D coverage was merely modelled in a cubic environment without any obstacles. Furthermore, the 3D sensing area of sensors was simply modelled as a spherical region.

On the other hand, in the area-based coverage problem, which is the concern of this research, the objective is to obtain the maximum region covered by sensors and is usually evaluated as the ratio of the covered area to the whole area (Huang & Tseng, 2005). The area-based coverage calculation methods are classified into: (1) methods that consider a raster environment (Akbarzadeh et al., 2013;Argany et al., 2012;Cortes et al., 2004), which are limited by the spatial resolution; and (2) methods that model the environment as a vector dataset (Ghosh & Das, 2006;Guvensan & Yavuz, 2011;Ma et al., 2009;Wang et al., 2006;Wang & Cao, 2011), which have been mostly proposed for 2D spaces and do not consider the changes in the topography of the area of study and the presence of human-made objects.

2.6.2. Sensor models

In general, there are two types of sensors: (1) sensors that focus on one point for data collection, such as temperature, humidity, and barometer sensors; and (2) sensors that have a specific range for tracking and collecting data, such as motion tracking and video sensors. In most research papers, the sensing range has been treated as a circle (Wang et al., 2006).However, event such a simple estimate of sensing range may change due to environmental factors such as rain and snow. For this reason, Phi et al. (2009) proposed an irregular range for sensors to represent a more realistic sensing capability.

In addition, sensor models can be directional or omni-directional. Omni-directional sensor models assume no limits of access in different directions, while in directional models such as video sensors, they may access only part of the directional range. Models can also be subdivided into binary and probabilistic models (Carter & Ragade, 2009). The difference between the two models is that if a target is located in a specific distance from a sensor, in the probabilistic model this target is described as being detected with a continuous probability between 0 and 1, but in the binary model, only the presence or absence of the target is described.

2.6.2.1. Omni-directional sensor model

The omni-directional model is generally represented as a circle in the two-dimensional state, but in the three-dimensional state it is represented as a sphere. This model is able to collect data from the environment in all possible directions and there are no restrictions in terms of its performance. Radio sensors for telecommunication are examples of these types of sensors.

2.6.2.1.1. Binary omni-directional model

If a sensor S node is in the position (x_s, y_s), in a two-dimensional configuration, its operating range is limited to a circle with radius R_s at center (x_s, y_s) (Figure 2.1). In this model, the sensor is able to track the targets that are inside this circle. If targets are outside this circle, the sensor is not able to track them. Therefore, in this model, a sensor can track the target with a probability of 1 when the distance between the target and the sensor is less than the radius of the sensor function. When this distance is greater than the sensor operating radius, the target is tracked with zero probability. If the target T is assumed to be in position (x_t, y_t), the probability of target detection by the sensor S in this model is obtained from the following equation.

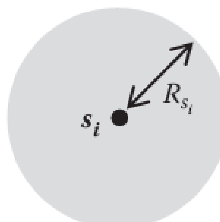


Figure 2.1: Omni-directional model of sensor (Argany et al., 2015).

$$P_{st}=\begin{cases} 1 & D_{TS}\leq R_s \\ 0 & Otherwise \end{cases} \tag{2.1}$$

Where P_{st} is equal to the probability of target tracking and D_{TS} is the Euclidean distance between target T and sensor S. This model is the simplest model that can be considered for the sensor. Similarly, a three-dimensional model can be defined in which the operating range is spherical.

2.6.2.1.2. Probabilistic omni-directional model

In this model, unlike the previous one, the visibility of a target as viewed by the sensor is given a probability value (Figure 2.2). No specific boundary can be considered for this model. In this area, the target is tracked with a probability between zero and one.

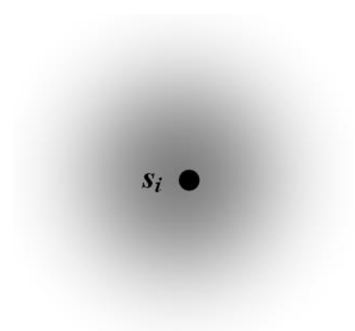


Figure 2.2: Probability omni-directional model of the sensor (Argany et al., 2015).

In this model, two main distances are considered for the sensor. The first distance is the same as R_s in the previous model. If the distance from the target to the sensor is less than R_s, the target is detected with a probability of 1. The second distance is R_u, which defines the range of uncertainty. If the distance from the target to the sensor is between R_s and $R_s + R_u$, the probability that the target will be detected by the sensor depends on the distance between them. If the distance between the target and the sensor is greater than $R_s + R_u$, the target will not be tracked by the sensor. The following equation describes how this model works (Akbarzadeh et al., 2011).

$$P_{st}=\begin{cases} 1 & D_{TS}\leq R_s \\ \dfrac{1}{1+exp\left[-\left(\frac{\lambda}{a}+\beta\right)\right]} & R_s<D_{TS}\leq R_s+R_u \\ 0 & R_s+R_u<D_{TS} \end{cases} \tag{2.2}$$

Here a is equal to D_{TS}-R_s, and λ and β are two constant values that express the hardware properties of the sensor. When the distance between the target and the sensor is less than R_s, the binary and probabilistic models act the same, and when the distance is between R_s and $R_s + R_u$, the probability model is gradually decreased. When the distance is greater than $R_s + R_u$, the probability is zero in both models. In the probabilistic model, when $\lambda = 1$ and $\beta = 1$, the slope of the changes is greater than when $\lambda = 0.5$ and $\beta = 0.5$. The probabilistic model is more realistic than the binary model, but most of the studies use the binary model for simplification.

2.6.2.2. Directional model

In the two-dimensional configuration, the model incorporates a viewing angle, so it covers only part of the space around it. These sensors can be placed in different directions and adapt the appropriate direction depending on the application. The features of a directional sensor are more relevant to reality in the three-dimensional state, but due to the complexities involved, most research efforts have treated it as a two-dimensional problem (Argany et al., 2011). The target is tracked by directional sensors when the following conditions are met:

$$\begin{cases} d(S,T)\leq R_s \\ \overrightarrow{ST}.\vec{d}\geq d(S,T)cos(\frac{\alpha}{2}) \end{cases} \tag{2.3}$$

Each directional sensor in the two-dimensional state contains four parameters P_s, R_s, d, and α. P_s specifies the position of the sensor in the area. R_s is the operating radius of the sensor, d is the direction of the sensor, and α is the viewing angle of the sensor. If α is 360 degrees in this model, this model becomes identical to the omni-directional model. Therefore, it can be concluded that the omni-directional model is a subset of the directional model.

2.6.2.2.1. Binary directional model

As explained in the previous section, the directional model, in addition to its range of distances, is limited in angle and direction (Figure 2.3). In a binary directional model, the distance range acts like a binary omni-directional model. if the target is in the distance range, it can be traced but if outside the distance range, it cannot be traced.

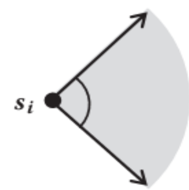


Figure 2.3: Binary directional model of sensor (Argany et al., 2015).

Using the conditions similar to those in Equation 2.3, the target is detected based on the direction and the angular range of sensors.

2.6.2.2.2. Probabilistic directional model

In the probabilistic directional model, the range of performance of the distance is similar to that of the probabilistic omni-directional model (Figure 2.4). With respect to the direction range, the more angle develops between the sensor direction and the target, the less likely it is to be detected.

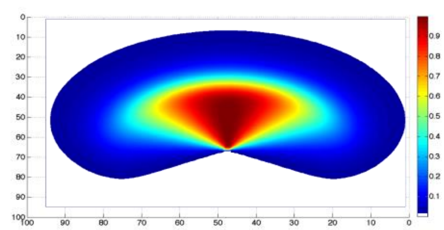


Figure 2.4: Probabilistic directional model of sensor (Akbarzadeh et al., 2013).

The probability function of the sensor direction (*P_α*) is defined in the two-dimensional and three-dimensional modes according to the actual performance that exists for the possible tracking of the sensor (Akbarzadeh et al., 2011) as expressed in Equation 2.4:

$$P_\alpha=\left(\frac{\cos(\alpha-\theta)+1}{2}\right)^{\omega} \tag{2.4}$$

where the parameter ω depends on physical characteristics of the sensor, the angle θ is equal to the operating angle of the sensor and α is the angle between the sensor direction vector and the target. As the ω decreases, the target tracking power increases.

2.6.3. Optimization algorithms

Generally, several methods (e.g., global or local, deterministic or stochastic) have been proposed to optimize the configuration of a sensor network based on maximum coverage criteria (Argany et al., 2011). In local algorithms such as the Virtual force-based Algorithm (Zou & Chakrabarty, 2003), the Potential Field-based Algorithm, and the 2D Voronoi Algorithm (Wang et al., 2006), the reconfiguration is done locally by changing the sensors' positions relative to the local environment and the presence of neighboring sensors. On the other hand, global algorithms such as the Genetic Algorithm (Romoozi & Ebrahimpour-Komleh, 2012), the Particle Swarm Optimization (PSO) Algorithm (Kulkarni & Venayagamoorthy, 2011), the Simulated Annealing (SA) Algorithm (Niewiadomska-Szynkiewicz & Marks, 2009), and the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) (Akbarzadeh et al., 2011) are used following a global design for sensor network configuration. These works with the global objective function of the whole network reconfiguration. In the following sections, we present both local and global optimization algorithms in more detail.

2.6.3.1. Local optimization algorithms

These algorithms use the concept of motion and the local displacement of sensors in the network. The optimization problem becomes a geometric problem and hence these approaches use a geometric data structure in order to increase network coverage. In local algorithms, the cost function of the network as a whole (e.g., its coverage) is not considered in the movement strategy of the nodes. In some of these algorithms, the cost function has been applied to control the stopping condition (stagnating time), allowing one to evaluate each step of the algorithm concerning whether or not it reduces the cost. Indeed, the aim of designing these algorithms is to move the nodes according to local information obtained from neighboring nodes at each location. In Yaagoubi et al. (2015), the structure of the environment has been used for the deployment of sensor networks. In this research, the Voronoi structure was applied in deploying cameras in a port. It was found that the cameras needed to be placed on the edges of the Voronoi cells for optimum coverage. However, in this research, the deployable area was not considered so that sensors could not be deployed in the center of pedestrian paths. In general, although these algorithms are fast and do not need to calculate the cost function many times in each iteration, they have limitations when one wants to apply multiple constraints, multi-objectives, and variations on sensor models. Examples of local algorithms for sensor network placement include the 2D Voronoi algorithm, the Potential Field-based, the Virtual Force algorithm, and the Incremental self-deployment (Li & Kao 2010; Wang et al., 2006; Zou & Chakrabarty, 2003).

2.6.3.1.1. The 2D Voronoi algorithm

In a 2D Voronoi algorithm, first the Voronoi diagram of the sensor points is formed. Depending on the number and density of sensors in the area, each sensor can cover all or part of its corresponding Voronoi cell. Due to the property of the Voronoi diagram, uncovered areas are formed at the vertices of the Voronoi (Figure 2.5).

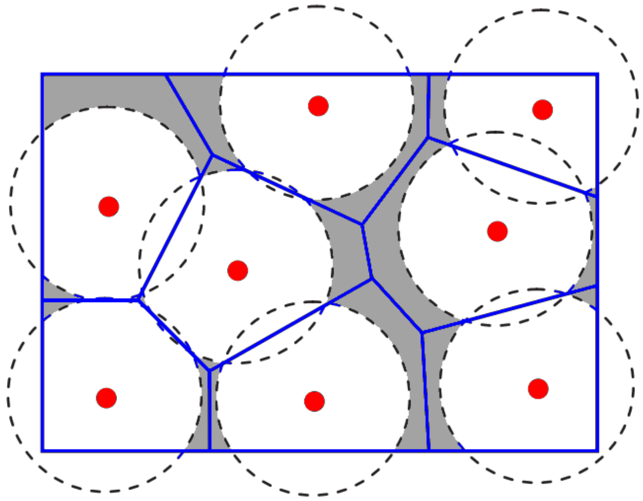


Figure 2.5: 2D Voronoi diagram of sensors; The gray area is the color of the uncovered holes created.

This algorithm moves each sensor toward its farthest Voronoi vertex to better cover this vertex (Figure 2.6). The Voronoi algorithm uses a tracking strategy so that the sensors may cover the maximum local cavity in their neighborhood (Argany et al., 2011). After moving a sensor, a new hole may form that fills with reverse displacement in the next iteration, causing oscillating displacement. Therefore, an oscillation control is added to overcome this problem, for example, it is stated that the sensor does not move in the opposite direction of its previous motion.

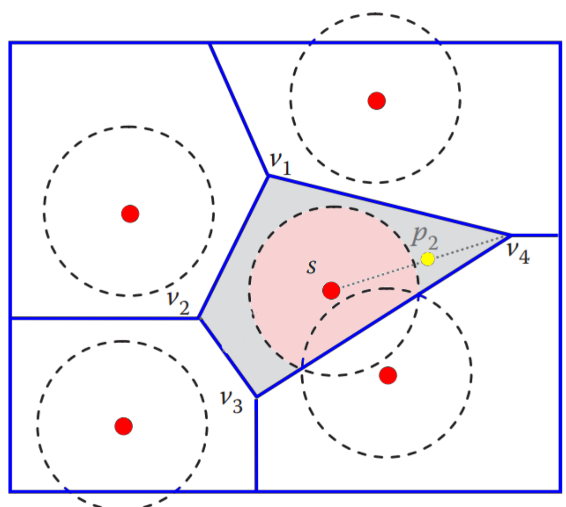


Figure 2.6: The strategy to cover the largest local hole of the sensor.

2.6.3.1.2. The Potential Field-Based Algorithm

The idea behind the Potential Field Based method is that each sensor faces two forces: 1) a driving force that causes the sensors to repel each other, and 2) the gravitational force that pulls the sensors together when the connections of sensors are about to be broken (Tao et al., 2007). These forces are inversely proportional to the square of the distance between the sensors. Each node repels all its neighbours. This action reduces the repulsive force but at the same time stimulates the gravitational force. Finally, in a particular arrangement, the algorithm is terminated so that all the sensors have reached a steady-state and have uniformly covered the desired area.

The Virtual Force-Based method is similar to the Potential Field-Based method in that each node faces three types of forces (Zou & Chakrabarty, 2003): 1) a repulsive force exerted by obstacles, 2) a gravitational force exerted by areas in need of high-grade coverage, and 3) the forces of gravity or repulsion exerted by other points based on their location and direction. The details of this algorithm will be elaborated in the next subsection.

2.6.3.1.3. The Virtual Force algorithm

The Virtual Force (VF) algorithm is a self-organizing algorithm that considers the obstacles and position of other sensors. This algorithm uses gravity and repulsion forces to move the sensors (Zou & Chakrabarty, 2003). It was inspired by closed disk theory (Locatelli & Raber, 2002) and uses concepts derived from robotics (Howard et al., 2002). The total force applied to the sensor S_i is indicated by the symbol $\vec{F_i}$ and the force applied by the sensor S_j to the sensor S_i is indicated by the force $\vec{F}_{ij}$. The force $\vec{F}_{iR_n}$ is applied to the sensor S_j as a repulsive force from the barrier R_n. The total force $\vec{F_i}$ on the sensor S_i is expressed as follows:

$$\vec{F_i}=\sum_{j=1,j\neq i}^{K}\vec{F}_{ij}+\sum_{n=1}^{N}\vec{F}_{iR_n} \tag{2.5}$$

where K and N are the number of sensors and obstacles, respectively. If in the location of the sensor network, the obstacles are simple and symmetrical in their shape and their number is known, their values can be easily calculated. The repulsive force exerted by the sensor S_j on the sensor S_i is obtained as follows (Zou & Chakrabarty, 2003):

$$f(x)=\begin{cases} 0, \ \ if\ d_{ij}\&>R_s \\ w\left(\left(\frac{1}{d_{ij}}-\frac{1}{R}\right),\alpha_{ij}+\pi\right), \ \ if\ d_{ij}\&\leq R_s \end{cases} \tag{2.6}$$

In the above equation, w is the weight of the force. The following equation is used to calculate the repulsive force exerted by obstacles on the sensor (Zou & Chakrabarty, 2003):

$$f(x)=\begin{cases} 0, \ \ if\ d_{iR_n}-r_{R_n}\&>R_s \\ \left(\frac{w}{d_{iR_n}-r_{R_n}},\alpha_{ij}+\pi\right), \ \ if\ d_{iR_n}-r_{R_n}\&\leq R_s \end{cases} \tag{2.7}$$

Where d_{iR_n} denotes the distance between the sensor and the obstacle. α_{ij} indicates the direction between the sensor S_i and the barrier R_n.

To obtain the new position of the sensor S_i with respect to these forces, the direction and magnitude of the output of all forces $\vec{F}_{xy}$ are used as follows:

$$\begin{cases} X_{new}=X_{old}+\dfrac{\vec{F}_x}{\vec{F}_{xy}}\times Maxstep\times e^{\frac{-1}{\vec{F}_{xy}}} \\ Y_{new}=Y_{old}+\dfrac{\vec{F}_y}{\vec{F}_{xy}}\times Maxstep\times e^{\frac{-1}{\vec{F}_{xy}}} \end{cases} \tag{2.8}$$

These methods, as described earlier, are for a situation where the position and number of obstacles are symmetrical and simple. However, when the forms of barriers are no longer simple and symmetrical, and their number is not initially determined (Doodman et al., 2014), a different method must be applied. For such a case, eight sensor neighbours may be used. The eight neighbourhoods could be applied in such a way that if there is an obstacle in any of these eight neighbourhoods with a fixed radius, a repulsive force is applied. Otherwise, there will be no obstacle-driven repulsive force on the sensor. The eight-neighborhood method leads not only to applying repulsive forces, but also escape forces, which are the result of gravitational forces from any one of the eight neighbourhoods which does not contain an obstacle. The escape force is the force that the sensor uses to escape from its surrounding obstacles. As shown in Figure 2.7, pixel *i* is the first pixel to be placed as an obstacle in one of the sensor's eight neighbourhoods. The repulsive force of this pixel on the sensor is calculated from Equation 2.7, under the constraint that the obstacle radius R_n is considered to be zero.

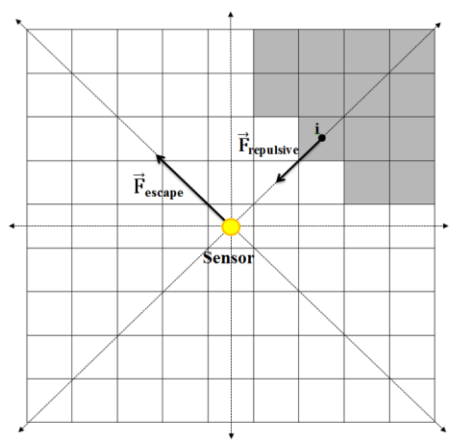


Figure 2.7: Eight-neighborhoods approach for VF algorithm.

2.6.3.1.4. Incremental Self Deployment

In the Incremental Self Deployment algorithm, each sensor finds its optimal location through the information concerning nodes placed in four steps (Howard et al., 2002b):

1. Initialization step, which classifies the sensors into three groups: waiting sensors, active sensors, and positioned sensors.

2. Goal selection step, which selects the best destination for the sensor being positioned based on the previous sensor position.

3. Goal resolution step, which assigns a new location to the waiting sensor and determines a plan to move to that location.

4. the Execution step, which locates the active sensors in place.

2.6.3.2. Global optimization algorithms

The goal of the global algorithms is to find the global optimum of a function called the objective function. These algorithms take into consideration the entire area of the sensor network that is, they use the entire search area to optimize the objective function. A distinctive feature of these algorithms is that they are random-based evolutionary processes. In all these algorithms, it is necessary to calculate the coverage as an objective function. In fact, the improvement of the coverage is carried out according to an estimation of the network coverage.

In general, global algorithms have been utilized for globally optimizing the configuration of the sensor network. In each step of these algorithms, the estimation of the objective function of each solution must be calculated to find out the next iteration of solutions (e.g., in the particle swarm optimization (PSO) algorithm, the objective function must be calculated for 100 solutions in each iteration; if the number of iterations is 100, the number of times the objective function must be determined is 10000. In this case, if the time execution for the objective function estimation is accomplished in 3s, the total computational time becomes 30000s). In general, these algorithms consume much more time compared to the local algorithms. The most important thing for these algorithms is that the objective function needs to be calculated for obtaining the optimal result for each iteration. In the next subsections, some of the optimization algorithms which use the global approach are discussed, including the genetic algorithm (GA), the PSO algorithm, the simulated annealing (SA) algorithm, and the Covariance Matrix Adaption–Evolution Strategy (CMA-ES).

2.6.3.2.1. The Genetic Algorithm (GA)

The GA is an evolutionary algorithm. It can be used for optimization problems with nondeterministic polynomial (NP) complexity. The complexity of optimization problems increases with the number of sensors (Ke et al., 2007). Hence, the sensor placement problem is an example of an optimization problem with NP complexity. There are many research papers that use genetic algorithms for the sensor deployment optimization. Jourdan and de Weck (2004) used a genetic algorithm to optimize network coverage as well as its lifetime. They saw a reduction in energy consumption as well as increase in grid life.

Jia et al. (2007) considered the issue of scheduling of the sensors network to increase the network's life. Their objective function seeks to maximize coverage and minimize covered area with more than one sensor. To extend the life of the sensor network, they determined the minimum number of sensors for achieving the optimal network coverage.

Wang et al. (2007) selected mobile sensors to improve the positioning problem using a genetic algorithm. Their objective was to increase network coverage and longevity. In this research, the positions of the sensors were treated as input variables in the optimization process. Therefore, the input variables for the genetic algorithm were the coordinates of the sensor nodes:

$$C=[x'_1,x'_2,\cdots,x'_N,y'_1,y'_2,\cdots,y'_N] \tag{2.9}$$

where, in this vector, N is equal to the number of sensors. The vector length of the variables is $2N$. In the first stage of this algorithm, the vectors of the variables were randomly generated by the number of populations defined in the genetic algorithm. The vector values of the variables were limited to the coordinates of the sensors, which must be within the bounding box.

At each iteration, the x and y coordinates combine between two different optimal solutions and also mutate randomly at a specific ratio. In each iteration, the variable vector that is most desirable is considered as the input to the next iteration. Two important stop conditions in this algorithm were: (1) no change in the network coverage in subsequent iterations; (2) reach the maximum desired number of iterations.

2.6.3.2.2. Particle Swarm Optimization (PSO)

The PSO algorithm is inspired by the movement of a flock (birds). It involves an easier implementation and fewer parameters to adjust than the genetic algorithm. The approach has been widely used in wireless sensor networks (Kulkarni & Venayagamoorthy, 2011) (for sensor deployment (Hong & Shiu, 2007), data integration (Veeramachaneni & Osadciw, 2008), and energy clustering (Cao et al., 2008)).

Particle swarm optimization algorithms have been used in the sensor placement problems for the optimization of both the network coverage and energy. Wang et al. (2009) used a particle swarm optimization algorithm to optimize the amount of energy needed to track targets. This algorithm was used to increase the coverage and reduce energy consumption by deactivating sensors that were far from the target.

Bai et al. (2009) have used the particle swarm optimization algorithm to optimize the position of sensors that were initially randomly deployed. Their objective was to optimize network coverage with minimal sensor movement. In all this research, a vector of the position of the sensors was defined as the population vector for the particle swarm optimization algorithm:

$$S_i=[x_1,x_2,\cdots,x_N,y_1,y_2,\cdots,y_N] \tag{2.10}$$

In this equation, x and y are the coordinates of the sensors and N represents the number of sensors. The velocity vector, an important component in this algorithm, is equal to the size of the population vector which allows the sensors to move toward the best local and global solutions at each iteration. In some of the research cited, the velocity range is considered as 1.4 tracking radii. In addition, the variables (coordinates of the sensors) should not be outside the bounding box.

2.6.3.2.3. The Simulated Annealing (SA) algorithm

The SA algorithm is a random algorithm. This algorithm is able to move from local to global optimization conditions. The main parameters are the rate of simulated temperature changes, initial simulated temperature, and movement size. The variable parameters are the position and direction of the sensors. The SA algorithm has been used in the sensor deployment optimization in the several research efforts, including:

Lin and Chiu (2005) proposed a simulated annealing algorithm to deploy the sensors to monitor target points, with the aim of reducing costs and increasing coverage. They used a grid environment for sensor deployment, while no obstacles were considered.

The use of the SA algorithm to increase network coverage was also implemented by Akbarzadeh et al. (2013). In their research, the environment model was considered as a raster model (including topographic information). This assessment has also been reviewed for areas of other sizes.

2.6.3.2.4. The Covariance Matrix Adaption –Evolution Strategy (CMA-ES)

The CMA-ES algorithm is another evolutionary algorithm. This covariance matrix algorithm upgrades the input variables for an optimal objective function. The performance of this algorithm is similar to the inverse Hessian matrix in Newton's method. For the sensor deployment problem, the position of the sensors as well as their direction are required as the algorithm seeks to place directional sensors (Akbarzadeh et al., 2010).

The parameters of the CMA-ES algorithm include the number of parents (μ), the number of generations (λ), and the mutation parameter (σ). The CMA-ES algorithm was used by Akbarzadeh et al. (2010) for a sensor placement problem that sought to increase network coverage. Their environment model was a raster model (including topographic information). This algorithm was compared with the SA algorithm for areas with different size characteristics. In their evaluation, CMA-ES showed a better performance than the SA algorithm.

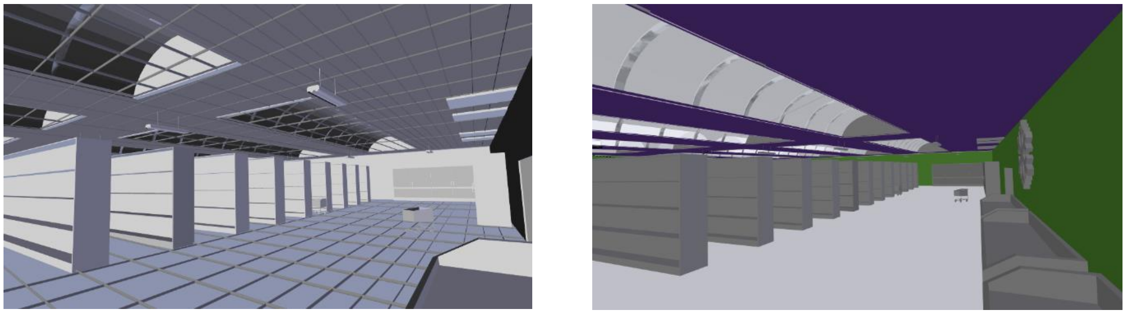
2.6.3.2.5. Limitations of local and global algorithms

In conclusion, local algorithms are heuristic approaches that require neighborhood information for sensors and their surroundings local environment. Although local algorithms need to determine the interactions between sensors and their surrounding environment, hence rendering computation demands complex, they do not need to calculate the sensor network coverage for a large number of solutions (sensor configurations) as in the case of global algorithms. This lack of coverage calculation makes the process of sensors deployment faster than when using global algorithms. In contrast, the global algorithms are able to incorporate new constraints (e.g., deployable area (walls and ceilings) in the indoor environment) and sensor characteristics (e.g., sensing limitations) into the process of sensor deployment because these algorithms only need to calculate the cost function iteratively and locally. In this regard, the cost function must be redefined in a way that the new constraints in the sensor deployment are addressed.

Regarding these advantages and disadvantages of local and global optimization algorithms, we propose to use a local algorithm with lower computation time and the minimum setting parameters, and exploit the advantages of global algorithms via the adoption of a cost function that takes better account of constraints and complexities in the sensor and environment models.

2.6.4. Environment issue

Most of the sensor coverage estimation methods use raster representation of the environment for optimization purposes. Raster representations, however, limit their precision and efficiency (Figure 2.**8**.a) (Akbarzadeh et al., 2013). This occurs because the raster representations are constrained by their spatial resolution, and their regular shapes result in redundant data for unoccupied areas (i.e. the unoccupied pixels are considered in the storage volume of raster data). Moreover, the raster-based approach cannot model the presence of solid objects, and columns inside the building. To overcome these limitations, we propose a sensor coverage estimation method based on a precise 3D vector-based representation of the environment (e.g., CityGML) (Figure 2.**8**.b).



(a) (b)

Figure 2.8: 3D (a) raster and (b) vector representation model

In other research (De Rainville et al., 2014), the voxel representation of the environment has been used for the deployment of camera sensors, for example within the context of the space station. The method ensures the ability to increase the high-density resolution of cameras using a cooperative algorithm and comparing the coverage output of the network with the help of the CMA-ES algorithm. The cooperative algorithm, proposed by Potter and De Jong (2000), decomposes the problem into sub-problems. The aim of this research was to minimize the difference between the sensing density of virtual cameras and the real density of cameras. The main problem encountered was not only converting the vector model to voxels, and to propagate the error that arises as a result into the coverage estimation, but the voxel model also incorporates redundant data in unoccupied areas. Also, although the modified cooperative algorithm considered the number of sensors in optimization, no constraints related to the deployable areas were included in this research (De Rainville et al., 2014). Indeed, in an indoor environment, sensors such as cameras might be readily deployed on the walls or ceilings while they cannot be deployed in any open space without physical support.

2.7. Conclusions

An overview of mobility issues for PWMD was presented at the beginning of this chapter. Following this, the dynamics of the environment and a discussion of the importance of sensor technologies was introduced. This led to a clear statement of the main issues for optimal sensor deployment. The coverage problem presents a significant challenge in sensor networks deployment. Optimization algorithms (both local and global) and environment models were introduced to address the issue. As discussed in this chapter, most existing methods oversimplify the environment and the sensor models and do not take into account the mobility of PWMD.

Optimized sensor network deployment is introduced as a promising approach for designing more adaptive and smart indoor environments to help PWMD during their mobility. This process is normally done by trial and error for mobility applications. However, sensors should be deployed in an optimal configuration for enhancing the satisfaction of people in their mobility. Sensors such as those designed for tracking can be used to monitor the dynamics of the environment (e.g., a person’s location, and locations of mobility obstacles such as people in motion). Although sensor network deployment has been intensively studied during the past decade, the majority of research efforts have considered only simple models of sensors (circles or spheres in the best case) and environments (2D, without obstacles) for achieving general objectives such as maximization of network coverage, or minimization of the cost of the network (Akyildiz et al., 2002; Ghosh & Das, 2006; Tubaishat & Madria, 2003; Wang et al., 2006).

Moreover, less work has been reported on the placement challenges posed by using multi-sensors (circular and directional, with different sensing range and heterogeneity features). Additionally, the majority of research has focussed on sensing in the outdoor environment. In the indoor environment, for example, the art gallery problem is considered for deploying a sensor network in a building in order to increase the coverage without considering the connectivity issues between the sensor nodes. Konda and Conci (2013) presented an optimization method for a cameras network deployed in order to achieve the maximum converge with high-quality image output by taking into account both the available light resources and obstacles within the indoor environment. Moreover, sensor deployment optimization on the ceiling of a building has been done for the indoor areas using simulation techniques (Kouakou et al., 2012).

In conclusion, sensor network deployment for the mobility problem has only been accomplished for individual interventions and has not, in general, considered the interactions between people and their surrounding complex environment during their mobility tasks. Hence, the main problem is how to place the sensors based on their characteristics as well as those of the indoor environment, the profile of PWMD, and the tasks involved in mobility to better assist PWMD to meet their needs during their mobility.

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3. Lisibilité personnalisée d'un environnement intérieur pour les personnes à mobilité réduite : un nouveau cadre

3.1. Résumé

Une carte mentale fait référence à la représentation personnalisée des connaissances spatiales dans l'esprit humain et est basée sur les perceptions, les expériences et les interactions des personnes avec leur environnement. Pour les personnes à mobilité réduite (PMR), certaines perceptions et interactions avec l'environnement au cours de leur mobilité se produisent de différentes manières et conduisent par conséquent à différentes cartes mentales. Par exemple, au cours de leur mobilité, ces personnes perçoivent et interagissent différemment avec les ascenseurs, les escaliers mécaniques et les marches. Par conséquent, leurs perceptions du niveau de complexité et de la lisibilité d'un environnement peuvent être différentes. La lisibilité d'un environnement est un indicateur qui mesure le niveau de complexité et la facilité de compréhension de cet environnement par une personne. Dans la littérature, la lisibilité est principalement estimée en fonction de facteurs environnementaux tels que la visibilité, la connectivité et la complexité de l'aménagement pour un espace donné. Cependant, le rôle des facteurs personnels (par exemple, les capacités) est rarement pris en compte dans l'évaluation de la lisibilité, ce qui complique sa personnalisation. Cet article vise à étudier l'influence des facteurs personnels sur l'évaluation de la lisibilité des environnements intérieurs pour les PMR. En plus de la visibilité, de la connectivité et de la complexité des environnements intérieurs, nous intégrons également l'influence du niveau d'accessibilité (c'est-à-dire la présence de facilitateurs et d'obstacles) dans le processus d'évaluation de la lisibilité. Le Centre des congrès de Québec a été choisi comme zone d'étude et la lisibilité de ce bâtiment a été quantifiée. Nous montrons comment l'intégration des facteurs mentionnés ci-dessus peut influencer la lisibilité des PMR et donc leurs performances de mobilité dans ces environnements.

Corps de l'article

Titre: Personalized Legibility of an Indoor Environment for People with Motor Disabilities: A New Framework

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3.2. Abstract

A mental map refers to the personalized representation of spatial knowledge in the human mind and is based on the perceptions, experiences, and interactions of people with their environment. For people with motor disabilities (PWMD), some perceptions and interactions with the environment during their mobility occur in different ways and consequently lead to different mental maps. For example, these people perceive and interact differently with elevators, escalators, and steps during their mobility. Hence, their perceptions of the level of complexity and the legibility of an environment may be different. Legibility of an environment is an indicator that measures the level of complexity and the ease of understanding of that environment by a person. In the literature, legibility is mostly estimated based on environmental factors such as visibility, connectivity, and layout complexity for a given space. The role of personal factors (e.g., capacities) is rarely considered in the legibility assessment, which complicates its personalization. This paper aims at studying the influence of personal factors on the evaluation of the legibility of indoor environments for PWMD. In addition to the visibility, the connectivity, and the complexity of indoor environments, we also integrate the influence of the level of accessibility (i.e., presence of facilitators and obstacles) in the legibility assessment process. The Quebec City Convention Centre was selected as our study area and the legibility of this building was quantified. We show how the integration of the above-mentioned factors can influence the legibility for PWMD and hence their mobility performance within those environments.

Keywords: personalized legibility; indoor environment; people with motor disabilities; mobility; cognitive map

3.3. Introduction

Enhancing social participation of people with disabilities (PWD) is a challenging issue for all societies. According to the United Nation's convention, "*persons with disabilities include those who have long-term physical, mental, intellectual or sensory impairments which in interaction with various barriers may hinder their full and effective social participation on an equal basis with others*" (Freeman et al., 2015). According to Statistics Canada (McClintock et al., 2016), 22% of the population aged over 15 years lives with a type of disability, representing 6.2 million Canadian citizens. A recent study on activity limitations, chronic diseases, and aging suggests that 33% of Quebec residents have some form of functional limitation and this percentage increases to more than 57% among people aged 65 or over (Statistic, 2016).

Mobility is one of the most important life habits of PWD and has a great impact on their social participation (e.g., going to school, going to work). The concept of mobility is defined according to different scales of locomotion such as daily walking, postural transfers, driving a car, and using public transportation (Fougeyrollas et al., 1998). Improving the mobility of PWD may significantly contribute to their social participation.

In this study, we are particularly interested in improving the mobility of people with motor disabilities (PWMD) who use wheelchairs in indoor environments by leveraging the potential of smart technologies. Recent advances in geospatial and communication technologies (e.g., smartphones, navigation, positioning technologies, sensor networks, actuators, Internet of Things, etc.) (Carver et al., 2016; Fallah et al., 2013; Kohoutek et al., 2010; Mnasri et al., 2018) allow us to design and develop more adapted and inclusive environments to facilitate the mobility of PWMD by guiding them to their destination and providing them pertinent information such as obstacles and facilitators on their path. The design and development of such inclusive environments necessitate the consideration knowledge on the perception, capabilities, experiences, and preferences of these people in their mobility and interactions with the environment. For instance, the ways PWMD that use wheelchairs for their mobility interact with objects such as stairs, doors, ramps, and other people, are very different than the general population. Hence the perception of these people on the complexity and legibility of the environment may not only differ from those of the general population but also among the PWMD themselves. The legibility of an environment is a key factor that influences the mobility performance of PWMD. In general, the legibility of an indoor or outdoor environment is defined as "*the ease with which its parts can be organized into a coherent pattern*" (Lynch, 1960). It contributes to the construction of a cognitive map, that is, a mental map of the environment which is used for navigation tasks (Weisman, 1981).

In the scientific literature (Li & Klippel, 2016; O'Neill, 1991), several factors are used to assess the legibility of an indoor environment including the level of connectivity, and the complexity of the indoor layout which can be measured using indicators such as the interconnected density (ICD) (Meilinger et al., 2012). However, other factors such as the level of the accessibility of the environment and the presence of landmarks (based on the location, color, and size) and informative elements (e.g., signage inside buildings) may significantly influence the legibility of the indoor environment for PWMD (Gharebaghi et al., 2018, 2017; Sharma, 2015; Vazquez et al., 2010). In addition to the environmental factors, the mobility of PWMD also depends on personal factors including their capabilities and experiences. To our knowledge, there are very few studies that explicitly take into account the personal factors when assessing the legibility of an environment for people with disabilities (Belir & Onder, 2013; Vazquez et al., 2010).

The research questions that are addressed in this paper are: (a) what are the most important factors to be considered for personalized legibility assessment for PWMD? (b) Is it possible to assess a personalized legibility for an indoor environment? In order to reply to these questions, we hypothesized that the legibility level of an indoor environment is significantly different for people with motor disabilities and can be personalized by considering the role of personal factors in the computation of each legibility factor (e.g., accessibility level).

This paper proposes a new framework for the assessment of the personalized legibility of indoor environments to better support the mobility of PWMD. For this purpose, relevant environmental and personal factors that influence the legibility of the environment for PWMD are considered. Our framework for the personalized legibility assessment for PWMD is based on the Disability Creation Process (DCP) model proposed by Fougeyrollas et al. (2019), as well as the notion of affordance that helps to better consider the role of personal factors in such a process. Personalized legibility assessment can provide indicators that lead to better designs and development of more accessible and legible environments using smart technologies (sensors and actuators) and can allow PWMD to better move and interact with their indoor environment.

The remainder of this paper is organized as follows. In Section 3.4, recent studies on the legibility of the environment are reviewed. Next, we propose a framework for modeling the personalized legibility of the environment that considers both environmental and personal factors in Section 3.5. Following this, in Section 3.6, the personalized legibility estimation approach is proposed. Then, to illustrate the proposed method for legibility modeling of an indoor environment, an experiment is carried out in Quebec City Convention Centre, one of the most complex buildings in Quebec City. Finally, discussions and conclusions are presented and future works are stated.

3.4. Literature Review

The legibility of the environment provides a link between human perceptions and the physical environment that influences the performance of wayfinding behavior. Lynch (1960) conducted a study of environmental legibility in support of wayfinding. He showed how distinct landmarks can affect the legibility of a city. His idea was introduced as the amount of suppleness that is necessary to recognize a coherent pattern from the surrounding environment. O'Neill (1991) proposed a conceptual model for legibility that introduced a cognitive map as an intermediary between the designed physical environment and wayfinding performance. A cognitive map is understood to be the mental representation of the environment that serves to indicate spatial and topological relations between connected places (Caduff & Timpf, 2008).

Generally, over the past several decades, researchers have been working on legibility of the environment using either qualitative or quantitative approaches (Wang et al., 2019). In the qualitative approaches, surveys and experiments are performed to statistically explore correlations between subjective assessments of legibility. For instance, O'Neill (1991) recruited 63 participants to determine the correlations between an environmental design factor (spatial and topological attributes of the building) and wayfinding performance mediated via the cognitive map. In earlier research, Günes (2018) evaluated the influence of environmental design elements, including signage, landmarks, the presence of an information desk, asking somebody, and familiarity, on the legibility of a shopping mall using self-reported data and qualitative experiments regarding wayfinding performance. On the other hand, quantitative approaches aim to model and simulate legibility within a more objective perspective. Most of the research efforts in this category have applied space syntax principles (e.g., visibility graph analysis (VGA)) in order to model legibility in wayfinding applications (Li & Klippel, 2016; Soltani & Ghasr, 2016). Recently, the visual saliency of images captured in indoor environments was used to quantify the legibility of indoor subway spaces using a deep learning approach (Wang et al., 2019). The focus of this research was the integration of both visuo-spatial and non-spatial attributes of the environment for legibility analysis.

Several legibility and complexity analyses of physical environments have also been reported in recent years in support of wayfinding applications. In general, the legibility factors addressed included: (1) visual access, (2) the level of connectivity, and (3) the level of complexity of the environmental layout. Low environmental visibility makes it more difficult to find the location of a destination. Benedikt (1979) used the isovist method for assessing the visual access of an environment. The level of connectivity is the degree of integration between convex spaces within a building. An axial map can be applied to measure the pattern of line-of-sight connections between spaces (Hillier & Hanson, 1989). Finally, the level of complexity is usually calculated based on the ICD, that is, the amount of complexity of a planar network structure. In fact, ICD represents the average degree of connectivity for each node over the whole network. Li and Klippel (2016) have applied these factors to suggest where the environment is more understandable. They integrated these factors into a definition of legibility.

There are other factors that influence the legibility of environments. Saliency is one of the factors that was mentioned in (Caduff & Timpf, 2008). Saliency concerns the distinction of prominent features with respect to other features. Saliency may include perceptual saliency, cognitive saliency, and contextual saliency. Perceptual saliency refers to the sensory predominance (e.g., visual, auditory, olfactory) and may include factors such as location-based attention (e.g., color, intensity), object-based attention (e.g., size, shape), and sensory context such as prevailing topological relationships. Cognitive saliency is related to human memory and experience, while the contextual saliency is changed in the different contexts. For example, when a person looks at a book in a library, books are more salient than other objects.

Furthermore, landmarks have been mentioned in several studies as important elements to create better linkages between survey and route knowledge (Carrera 2017; Dahmani et al., 2012; Lin et al., 2014; Patel & Vij, 2010; Raubal & Winter, 2002; Siegel & White, 1975). In fact, landmarks are distinctive features that serve as reference points for navigation so as to orient users based on the surrounding environment. Although landmark saliency is assessed based on the performance of wayfinding by people in the environment (Caduff & Timpf, 2008), it has not been integrated so far with other factors such as visibility, connectivity, and complexity to evaluate the legibility of indoor environments. Indeed, the saliency of an object is among the characteristics that help people to identify them as landmarks. It allows landmarks to be distinguished from their context and used as reference points during navigation tasks.

Regarding personal factors in legibility analysis, especially the capabilities of PWD, a few studies have been carried out, but most of these have been focused on people with visual impairments. As an example, Belir and Onder (2013) investigated the spatial organization of an indoor shopping mall and how this was influenced by structural and sensory landmarks (e.g., corridor entrances and odors coming from trash bins, respectively). They concluded that these landmarks influenced the legibility of a place, especially for people with visual impairments. In their research, integration using axial line relationships (number of intersections) and connectivity using visibility graphs (number of connected points) were used to verify the legibility of landmarks by people with visual impairments. The researchers found out that the high integration and connectivity between structural and sensory landmarks significantly impacted the cognitive maps of people with visual impairments.

To the best of our knowledge, modeling the legibility of indoor environments for PWMD has not been studied, even though the related issue of accessibility has been addressed in both outdoor and indoor environments. Accessibility is the degree to which an object can be reached or approached (Welage & Liu, 2011). Like legibility, the level of accessibility of an environment may impede the mobility behavior of people using wheelchairs or, alternatively, may facilitate their movement. According to the Americans with Disabilities Act Accessibility Guidelines (ADAAG) (Leonard, 2000), for accessibility analysis, indoor spaces are classified into: (1) primary path segments, (2) secondary path segments, (3) closed space-like rooms, (4) open space-like corridors, (5) doors, (6) stairways, (7) elevators, (8) ramps, and (9) furniture. Most recently, Yaagoubi et al. (2020) proposed a new method based on the Voronoi data structure to obtain a navigational network for PWMD using the ADAAG classes and IndoorGML standards (Li et al., 2019). Additionally, Park et al. (2020) investigated the accessibility of the navigational networks of two shopping malls using a new extension of IndoorGML. Drawing upon the American Disabilities Act (ADA) and the Barrier-Free Certification System (BFCS), they classified indoor spaces and their accessibility attributes into: (1) corridors (area, width, slope, and level change attributes), (2) elevators (area, passing width, and control buttons), (3) escalators (with ramp), (4) stairways (with wheelchair lift and ramp), (5) ramps (width, slope, turning width, and handrail), and (6) doorways (directions including push and pull, the existence of automated functions, width, height, and sill-like flats).

We consider that the aforementioned elements may have a significant impact on the legibility of an indoor environment for PWMD based on their personal experience and interaction with the environment. Hence, in the following section, we propose a novel framework for the analysis of the legibility of an indoor environment for the mobility of PWMD.

3.5. A New Conceptual Framework for the Assessment of Personalized Legibility for PWMD

We consider that the legibility of an environment is affected not only by environmental factors but also by personal factors such as personal capabilities and preferences. As mentioned earlier, several factors such as the degree of visual access, the connectivity, and the ICD, a measure of the complexity of an indoor environment, are already presented in the literature (Li & Klippel, 2016). However, these factors need to be extended to also address the interaction of personal factors (e.g., personal capabilities, experiences, and perceptions). For example, for a blind person, legibility of an environment in terms of visibility may be null. Indeed, for a person with visual disabilities, visibility graphs or isovist methods (Turner, 2004) cannot be used for legibility assessment. In addition, for a person with motor disability, such as someone using a wheelchair, visibility may change as a function of wheelchair height and hence the person will have a different visual perception of the environment. Consequently, the legibility will also be different. Hence, legibility should be considered as a two-way factor computed in interaction between personal and environmental factors.

Legibility is perceived by PWMD based on their interactions with the environment, their individual sensory capacities, impairments, identities, and their confidence while they move about in the environment. For instance, although PWMD do not usually have problems with sensory inputs, their point of view can vary based on factors such as the height of their wheelchair seat. In this case, visibility may be confined to some directions. Regarding identity issues, such as age, education, etc., these factors could affect the significance of different environmental factors. Furthermore, path accessibility may have an impact on stress levels of PWMD, thereby affecting the legibility and complexity of the environment.

Our framework for assessing the legibility of the environment integrates the Disability Creation Process (DCP) model proposed by Fougeyrollas et al. (2019) as well as the notion of affordance to help better consider the personal factors in such a process, especially for PWMD. According to the DCP model, disability is defined as a result of interactions between people and their environment. This model incorporates multiple environmental factors, from fully facilitating to fully impeding, in interaction with personal factors. Personal factors include identity, the health status of a person's organic systems, and capabilities that are scaled from facilitating to impeding, integral to impairment, and ability to disability. The notion of obstacles and facilitators is defined based on the interactions between personal and environmental factors. For instance, a stairway can be considered as an obstacle for certain PWMD based on their capabilities. Hence, we argue that legibility can be considered as a result of interactions between people and their environment, when these are oriented towards a specific purpose (i.e., carrying out a life habit such as mobility). Figure 3.1 illustrates our idea for the integration of the legibility concept into the DCP model for mobility purposes.

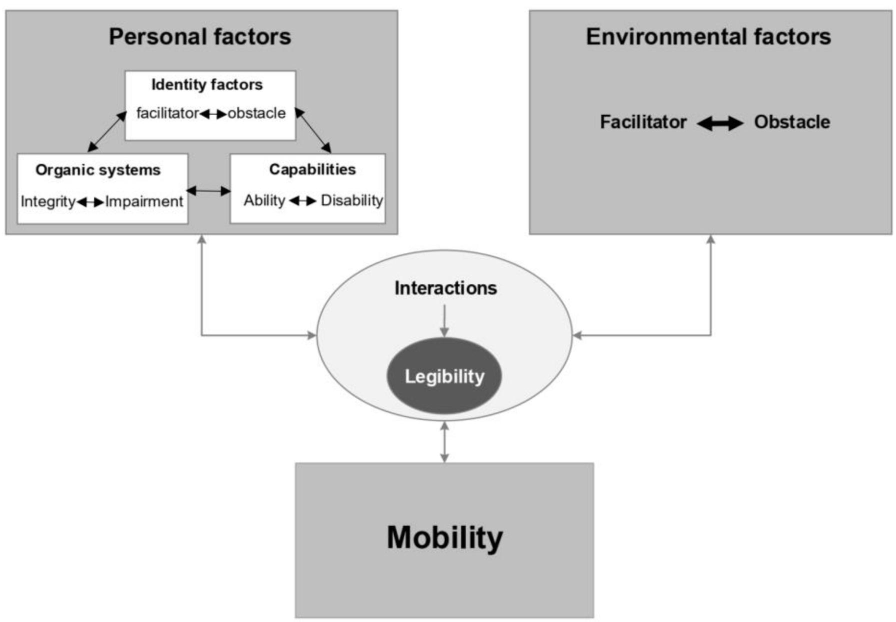


Figure 3.1: Legibility as a result of interactions between personal and environmental factors for mobility tasks in the Disability Creation Process (DCP) model.

Several attempts in computer science (e.g., agent models) and psychology (e.g., cognitive models) have been undertaken to measure how a person interacts with his/her surrounding environment (Lewis, 1998; Yaagoubi & Edwards, 2008). For instance, sense–plan–act is one of the frameworks that has been proposed in the robotics field to define the interaction between an agent with its surrounding environment (Gat et al., 1998).

According to this approach, a person has the ability to sense and perceive the environment and its dynamics and to extract the required information for subsequent plan and action. This process iteratively defines the interactions of the person with his/her environment and contributes to the creation of a cognitive map of the environment and its update, which provides a personal sense of legibility of the environment in support of the mobility task (Figure 3.2).

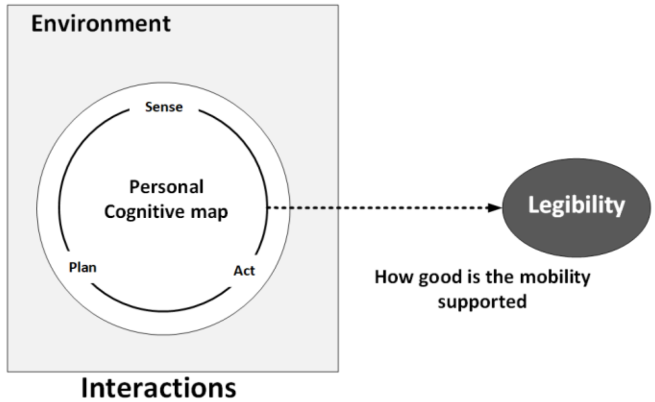


Figure 3.2: Relation of legibility and human–environment interactions.

Regarding the process of planning and acting in wayfinding behavior, affordance and information processing are the two main aspects that help people to choose the right way among alternatives (Raubal, 2010). Based on Gibson's theory (1994), affordance consists of how environmental elements offer the possibility of action. For example, in the wayfinding domain, corridors offer “go-to” affordances. Information, on the other hand, reflects knowledge of the destination from orientational aids and informative signs in a building. People with this knowledge are better able to find their destination in a short time, via accessible ways, and with low cognitive load. According to Niesser’s model (1976), the appropriate information is picked up based on schemas registered in people's minds. Hence, it is necessary to include semantic data to estimate the legibility of the environment for each individual who strolls around inside the building. According to our proposed framework and the relevant literature on legibility, factors that should be taken into consideration include the level of visual access, the level of connectivity, the level of complexity of building layout, and the level of accessibility (facilitators/obstacles):

1. *Level of Visual Access:* one indicator that influences the estimation of legibility is visual access. Generally, better visual access to a location implies better legibility. Based on Niesser's theory (1976), perception leads to mental representation via a person's visual schemas. In the creation of such schemas, the location of people, the orientation of the head, and their visual competency are used as components for the person's situation awareness. In addition, obstacles such as walls and furniture may lead to limitations in visual access. Although visual access is a common factor that influences legibility for most people, for PWMD, however, this may be significantly different as they have different and, in some cases, restricted visual access to the environment. This is partly because they use wheelchairs for their mobility and hence perceive the environment from a different angle compared to a person who walks.

2. *Level of Connectivity:* another key factor in determining legibility is the connectivity between the spaces. This is also called the degree of spatial integration (Hillier & Hanson, 1989). This factor quantifies the degree to which people come together in one place from other places. Legibility is inversely related to the degree of connectivity. The more people converge into one space, the more they may become anxious and confused about their goals. The number of axial connections between convex spaces can provide a way to calculate the degree of connection of spaces, especially in indoor environments. This factor is important for both people with and without disabilities. Intersections of the corridors are among the most important decision points in indoor environments during the mobility task. However, personal capabilities and spatial reasoning skills, as well as personal factors such as age, can differ from one person to another.

3. *Level of Complexity of Building Layout:* the complexity of a building's layout was initially determined by O'Neill to contribute to the legibility of indoor environments. Complexity can be characterized based on the result of the analysis of topological/neighbor relations between the interior spaces (rooms, corridors, etc.) of a building. For this purpose and based on graph theory, a path is divided into several sub-components between decision points. Several studies in the past decade have focused on automated methods to segment and categorize indoor environments, with emphasis on: (1) skeletons (medial axis transformation) (Lee, 1982), (2) regular tessellations (Kostic & Scheider, 2015), (3) irregular tessellations (Afyouni et al., 2012), (4) visibility graphs (Turner et al., 2001), and (5) variable density networks (Boguslawski et al., 2016). Although most of these methods have sought to create navigational graphs for the general public, the AccessVOR (Yaagoubi et al., 2020) method has been adapted to address the accessibility issues of PWMD based on the ADAAG standards. The graph density at each point determines the degree of its complexity indicated by ICD that should be considered in the legibility assessment. The complexity factor may also impact the legibility of the indoor environment differently from the perspective of PWMD. For instance, the number of corridors intersecting at a point may imply a more significant presence of people moving in different directions and hence create a mobility obstacle for the PWMD, which may be less constraining for other people without disabilities in the same situation.

4. *Level of Accessibility (Obstacles/Facilitators):* The main factor for determining the legibility of the environment, for PWMD, is related to their level of accessibility to such an environment. Facilitators such as elevators and obstacles such as stairs have a large salient impact on a person who uses a wheelchair compared to other environmental elements. In general, each object in the environment offers some level of obstruction or facilitation with regard to mobility performance. Several studies classify environmental entities for assessing the accessibility of a path for PWMD in indoor

environments. For instance, a path with specific slope, width, and level change attributes can appear as an obstacle for PWMD. Most recently, Park et al. (2020) classified indoor spaces and their accessibility attributes into:

- Corridors (area, width, slope, level change)
- Elevators (area, passing width, and control button)
- Escalators (with ramp)
- Stairways (with wheelchair lift and ramp)
- Ramps (width, slope, turning width, and handrail)
- Doorways (directions including push and pull, the existence of automated functions, width, height, and the presence of sill-like flats)

Based on the characteristics of obstacles and facilitators, the degree of accessibility and legibility of the environment for PWMD are determined. There is an index accessibility assessment approach (Gharebaghi et al., 2017) that considers facilitators (e.g., ramp) and obstacles (e.g., high slope) based on the confidence level of PWMD on the path. This approach is based on the route knowledge. However, for assessing legibility, the survey knowledge is also significant. For instance, when a person with a wheelchair encounters an obstacle, he/she must look for another path, especially a path that uses facilitating elements such as a ramp and not an escalator. Hence, the presence along the way of elements with different affordances for an individual with or without disabilities affects the legibility of the environment.

There are other embedded elements such as landmarks and informative elements by which the mobility performance can be facilitated. Landmarks facilitate the route-finding process because they are prominent objects in the environment that enrich knowledge about routes (Lynch, 1960). Landmarks are objects that are more easily identified than other objects. Their distinctiveness is based on their size, color, and location within the human mental representation. Landmarks are categorized into visual (extended to sensory (Belir & Onder, 2013)), structural, and cognitive landmarks (Sorrows & Hirtle, 1999). Regarding sensory landmarks, other than the objects themselves associated with paths (structural) and mental representation (cognitive), smells and features sensed by other means could be used as referents during navigation. What is considered a landmark varies among people based on their experience and interactions. According to several studies on spatial cognition, landmarks have a significant role to play in creating a cognitive map (Caduff & Timpf, 2008). In general, landmarks can be captured from a person's in situ perspective view or via a two-dimensional overview of a given route (using a map) as a set of references for the route. The first of these is called the egocentric frame and the second is the allocentric frame (Yaagoubi & Edwards, 2008). In general, regardless of which frame is adopted, the presence of landmarks in human visual, linguistic, and spatial memory play a significant supportive role in navigation.

Informative elements are divided into two categories: orientation aids and informative signs (Darken & Peterson, 2014). Orientation aids include information desks, maps, and site plans, whereas informative signs consist of identification signs (indicating pertinent names and symbols) (Arthur & Passini, 1992) and directional signs (indicating the direction that people need to move using arrows and pictograms) (Miller & Lewis, 1999). The presence of these elements is vital to understanding the environment, especially in unfamiliar locations. Not only do these elements need to provide accurate and sufficiently detailed information about the environment and directions, but they must also be easily recognizable via their colors and locations. In our study, the focus is mainly on the detection of signs and their locations as well as their visual saliency, not on their content.

Visual saliency is one of the attributes that can be used to measure the level of differentiation of an object from its surroundings (Caduff & Timpf, 2008). The degree of differentiation of landmarks and signs as mobility facilitators and obstacles can be assessed for each person according to his/her position. This degree of differentiation varies depending on the individual, the location, the time, and the context. It can be calculated by considering the person, the wheelchair's location, and the image perceived, as a function of his/her position. In general, visual saliency "[…] *is the distinct subjective perceptual quality which makes some items in the world stand out from their neighbours and immediately grab our attention*" (Itti, 2007). Hence, the measurement of visual saliency aims to identify the regions in an image that would attract a person's attention. Generally, the human visual system involves a selection process that does not include all the visual information in an image. Many studies have focused on developing models of visual attention (Bruce & Tsotsos 2006; Gao & Vasconcelos, 2005; Harel et al., 2007; Hou & Zhang, 2007; Itti & Koch, 2001; Judd et al., 2009; Rao et al., 2002). These models are divided into top-down and bottom-up methods. Top-down models are related to human cognition and view attention as a task-dependent behavior, based on memory, reasoning, etc., whereas bottom-up models are based on the scene attributes that attract attention in terms of motion, contrast, intensity, color, orientation, etc. On the one hand, the first group considers which part of a scene is "relevant" based on the task and motivation. On the other hand, "*saliency*" is considered to be a stimulus driven from external objects. The bottom-up models have attracted a lot of interest in many studies over the past decade as a means to quantify human visual attention and visual saliency within image processing.

Hence, the visual saliency attribute needs to be added to the category mentioned by Park et al. (2020) for measuring the level of accessibility of obstacles and facilitators. As can be seen in Figure 3.3, the staircase is viewed as an obstacle with high visual saliency by a person with a wheelchair while the elevator is not visually salient. The level of accessibility is one of the most important factors that need to be considered, especially for PWMD, as obstacles and facilitators may limit or help their mobility, respectively. Hence, this factor plays an important role in personalizing the legibility assessment of an indoor environment.

(a) (b)

Figure 3.3: Visual saliency of (a) stairs and (b) elevator in an intersection at the Geomatics Department, Quebec City.

To sum up, in this section, legibility was conceptualized based on the interactions between a person and the environment. These interactions may be understood to constitute an iterative sense–plan–act process, and generate a cognitive map for mobility performance. Furthermore, several factors that have an impact on the legibility of the environment for PWMD were introduced. The legibility for PWMD based on these contributing factors is estimated in the next section.

3.6. Estimation of the Personalized Legibility for PWMD based on the Proposed Framework

According to the proposed framework for legibility assessment for PWMD, a legibility estimation approach is developed. This utilizes the level of visibility access, the level of connectivity, the level of complexity of building layout, and the level of accessibility (facilitators/obstacles) factors (Figure 3.4). The inputs for each of these include a 2D building plan, a navigational network, a trajectory, and a geo-tagged video. Among these inputs, the trajectory and geo-tagged video are used for determining the visual saliency with respect to location and direction of a person with motor disability. Effective methods for estimating visibility access, connectivity, complexity, and the level of accessibility (facilitators/obstacles) and their integration are presented in the following section.

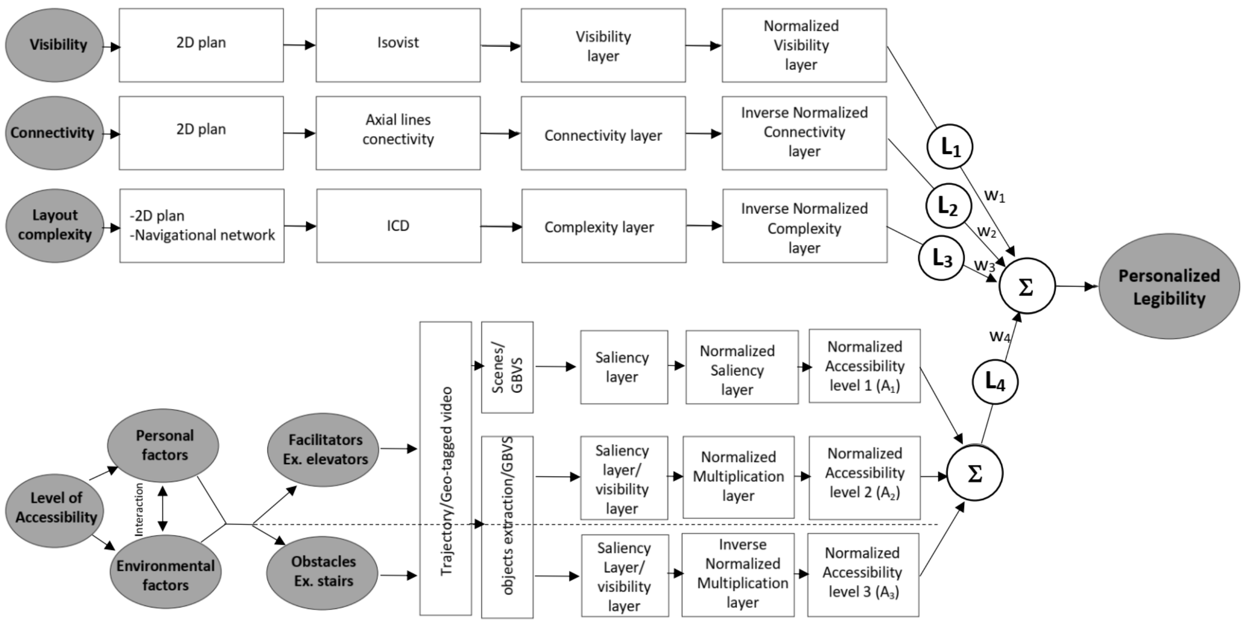


Figure 3.4: Estimation of personalized legibility of an indoor environment for people with motor disabilities (PWMD).

The following paragraphs briefly present the computational aspect of our method.

a) In order to calculate visibility access, a visibility layer is created using a 2D plan. From this, the isovist method (Benedikt, 1979) is used to indicate different levels of visibility in any location on the map. Isovist refers to the calculation of the visible region of the environment from a given viewpoint (Figure 3.5).

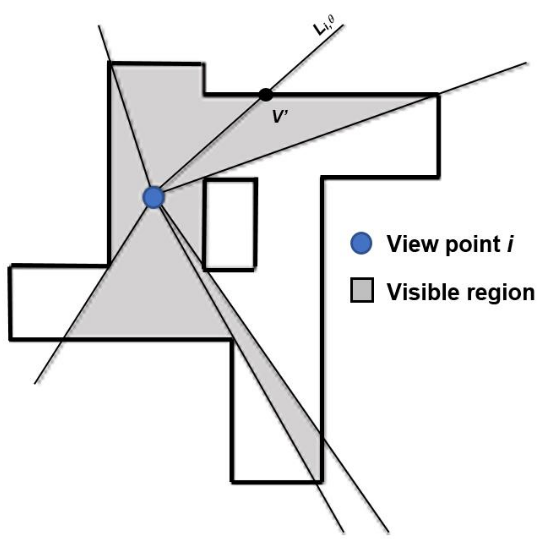


Figure 3.5: Visible region from the viewpoint *i*.

The area of such a visible region is considered as *Isovist* for each viewpoint. A 2D building plan includes the walls and obstacles that obscure the lines of sight. The visible area for viewpoint *i* and the *Isovist* are calculated as follows:

$$Visible_i = \{v \in R: v \text{ is visible from viewpoint } i\}, \quad (3.1)$$

$$Visible_i = \{[i,v'] : v' \in L_{i,\theta}\}, \quad (3.2)$$

$$Isovist_i = Area\ (Visible_i) \quad (3.3)$$

$$L_1 = Normalize\ (Isovist\_layer) \quad (3.4)$$

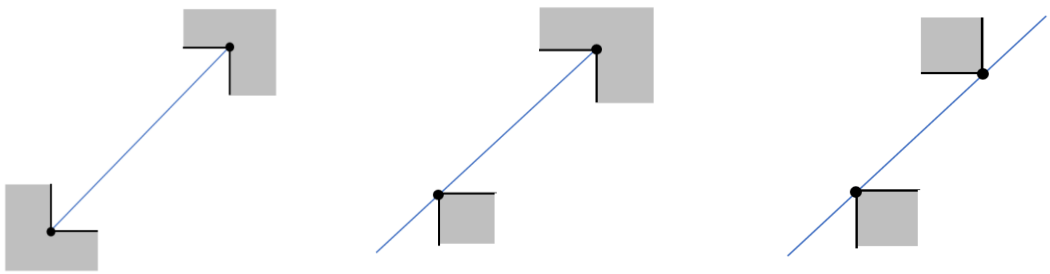
where *v* is any visible point in *R* (2D space) from viewpoint *i* and *v'* is the set of visible boundary points that can be determined based on the ray tracing boundary $L_{i\theta}$ from viewpoint *i*. The *Isovist_layer* is the *Isovist* value of all the grids across the entire area. L_1 denotes the first normalized legibility factor. The normalization is done so that the data are shifted and rescaled into a range of 0 to 1. This normalization process leads to the data maximum and minimum being converted into 1 and 0, respectively.

b) The level of connectivity is calculated based on the axial lines. An axial line is any line that links two inter-visible vertices inside a space (Figure 3.6). Via the number of intersections for these lines, the connectivity between spaces is determined. There are three cases to be considered: (1) both vertices are convex, (2) one is convex and the other is reflexive whereby the line can be extended through the space, (3) both are reflexive as and the line is extended from both vertices (Figure 3.6). The connectivity is calculated based on the number of intersections between one axial line and the other axial lines.

$$Connectivity_i = Number\_of\_intersections\ (\text{the nearest Axial line, Axial\_lines, point } i) \quad (3.5)$$

$$L_2 = Inverse\_Normalize\ (Connectivity\_layer) \quad (3.6)$$

where $Connectivity_i$ is the number of intersections of the nearest *axial_line* to point *i* and other *axial_lines* and L_2 denotes the second inverse normalized legibility factor that includes the connectivity values of all the grids in the entire area. The inverse normalization is done so that the data are shifted and rescaled in the range of 1 to 0. This function converts the maximum and minimum into 0 and 1, respectively. The inverse process is chosen because of higher connectivity decreases legibility.



(a) (b) (c)

Figure 3.6: Three cases of axial lines generation, (a) convex–convex, (b) convex–reflexive, (c) reflexive–reflexive.

c) The complexity of building layout is calculated based on the interconnected density (ICD) of a navigational graph. The ICD of a vertex of a graph is the number of edges that reach to the vertex. For example, as illustrated in Figure 3.7, the ICD varies from 1 to 4 for each vertex. A higher ICD shows higher complexity of the graph at each vertex, which also indicates the complexity of the building layout.

$$ICDi=Degree\_of\_graph\ (Navigational\ graph,\ the\ nearest\ node\ to\ the\ point\ i) \tag{3.7}$$

$$L_3=Inverse\_Normalize\ (ICD\_layer) \tag{3.8}$$

where *ICDi* is the complexity of the layout calculated based on the degree of the nearest node of the navigational graph to point *i*. L_3 denotes the third inverse normalized legibility factor. The inverse is chosen because higher complexity corresponds to decreased legibility.

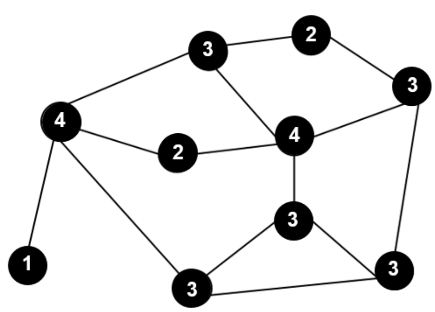


Figure 3.7: Interconnected density (ICD) of each vertex in a graph.

d) The level of accessibility is calculated based on the facilitators and obstacles according to the interactions between PWMD and the environment. In addition to object classification into facilitators and obstacles, the visual saliency each scene perceived and attended by a PWMD in situ is a facilitator for him/her, which increases the legibility of environment.

The calculation of visual saliency is carried out for each frame of a geo-tagged video on a trajectory using visual attention models (Figure 3.8). Borji and Itti (2012) divided the visual attention models into eight classes: (1) Bayesian: learning based on past experience to find target features, (2) cognitive: use of band-pass filtering such as via a difference of Gaussians (DOG) algorithm that corresponds to attention as measured by psychological experiments (Itti & Koch, 2001), (3) decision theories: these models are based on people's decision-making processes, they are a combination of top-down and bottom-up models of human attention (e.g., Gao and Vasconcelos (2005)), (4) graphical: probabilistic models that estimate the dissimilarity probability for each region in relation to other regions such as the graph-based visual saliency (GBVS) algorithm (Harel et al., 2007), (5) information theoretic: based on the most informative part of an image (Bruce & Tsotsos, 2006), (6) pattern classification: these models employ a machine learning process to extract the salient parts of a new image based on eye fixation datasets and labelled salient areas in image databases as training datasets (Judd et al., 2009), (7) spectral analysis: converting the image into the frequency domain and capturing salient parts in this domain (Hou & Zhang, 2007), and (8) other categories (Rao et al., 2002). According to Sharma (2015), of the eight categories, the GBVS algorithm (#4) gives the best results observed without training datasets, based on correlations between image features and observed eye saccades obtained for humans. As a consequence, this result led us to consider this algorithm for the visual saliency analysis. Based on the GBVS algorithm, the visual saliency of each position on the trajectory is formalized with the ratio of the sum of pixel saliency to the number of pixels in a frame.

$$S_k(i, j)=GBVS(Frame_k(i,j)), \qquad k=1,\dots , n \tag{3.9}$$

$$SP_k=(\sum_i^{m_1}\sum_j^{m_2} S_k(i, j))/m_1 * m_2), \qquad Trajectory= \{p_1, p_2,\dots,p_n\} \tag{3.10}$$

$$A_1= Normalize\ (SP_k\_layer) \tag{3.11}$$

where S_k is the saliency array of Frame k and n the number of frames recorded for a geo-tagged video in Equation (3.9). In Equation (3.10), SP_k is the saliency of position k on a trajectory, i, j show the position of pixels, and m_1 and m_2 are the frame's width and height, respectively. A_1 is the first normalized factor for the accessibility assessment.

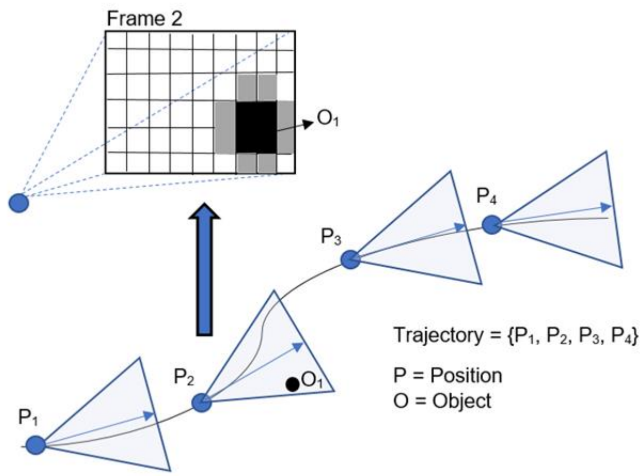


Figure 3.8: A geo-tagged video recorded on a trajectory for visual saliency calculation.

In order to assess the accessibility level of each segment of a route for PWMD legibility assessment, firstly, we need to identify and detect all environmental factors affecting mobility. These factors may include both obstacles (e.g., slopes, steps, etc.) as well as facilitators (e.g., signs, elevators, etc.). It is important to mention that the concepts of obstacles and facilitators are not absolute characteristics of objects and may vary from one person to another depending on the nature of the interactions that people may have with those objects. In this work, these elements are identified based on their visibility and visual saliency inside each frame of the geo-tagged video. Based on our team's previous work (Gharebaghi et al., 2017), the accessibility level of each route segment is estimated using a confidence-based approach. This means that we ask PWMD to indicate their confidence level to carry out a mobility task in the presence of an obstacle (e.g., ramp with a certain slope value, steps, etc.) or facilitators (e.g., signs). Of course, this level of the confidence is dependent on a person's capabilities, experiences, and personal skills. Hence, the accessibility level of a given route segment is evaluated based on the results of the interactions between personal factors and the environmental factors and varies from one person to another. The level of accessibility in the presence of obstacles and facilitators is then scaled from 0 to 1 (Equation (3.12) and (3.13)).

Secondly, the visual saliency of each frame is calculated based on the GBVS algorithm (Figure 3.9b) (Equation 3.10). Thirdly, the ratio of object pixels to the total number of pixels in the frame is used to determine visibility (Equation (3.16) and (3.17)). Visual saliency is then summed over each object pixel in the frame to estimate the total saliency (Equation (3.14) and (3.15)). For each position on the trajectory, the visibility and saliency of each object are determined. In order to integrate these, they are normalized (facilitators) or inverse normalized (obstacles) and multiplied by each other to measure the accessibility level of each object for each position on the trajectory (Equation (3.18) and (3.19)). In the final step, all the accessibility levels are combined to create a layer that shows the accessibility level of facilitators and obstacles at each location of the building layout.

$$F_k(i, j)=(Confidence\_level/100)*Facilitators\_extraction(Frame_k(i,j)), \quad k=1,\dots, n \tag{3.12}$$

$$O_k(i, j)=(1-Confidence\_level/100)*Obstacles\_extraction(Frame_k(i, j)), \quad k=1,\dots, n \tag{3.13}$$

$$SaliencyF_k=(\sum_i^{m_1}\sum_j^{m_2} S_k(i, j) *F_k(i, j))/(\sum_i^{m_1}\sum_j^{m_2} F_k(i, j)), \quad Trajectory=\{p_1, p_2,\dots,p_n\} \tag{3.14}$$

$$SaliencyO_k=(\sum_i^{m_1}\sum_j^{m_2} S_k(i, j) *O_k(i, j))/(\sum_i^{m_1}\sum_j^{m_2} O_k(i, j)), \quad Trajectory=\{p_1, p_2,\dots,p_n\} \tag{3.15}$$

$$VisibilityF_k=(\sum_i^{m_1}\sum_j^{m_2} F_k(i, j))/m_1 * m_2), \quad Trajectory=\{p_1, p_2,\dots,p_n\} \tag{3.16}$$

$$VisibilityO_k=(\sum_i^{m_1}\sum_j^{m_2} O_k(i, j))/m_1 * m_2), \quad Trajectory=\{p_1, p_2,\dots,p_n\} \tag{3.17}$$

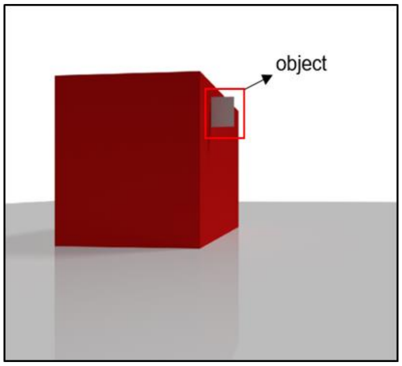
where F_k and O_k are the layers in the range between 0 and 1, and show which pixels are and are not part of a given object, with the indication the accessibility level based on the confidence level of PWMD (*confidence level* is scaled between 0 and 100%). For instance, the confidence level of a PWMD to move with a wheelchair in a segment with the presence of a sign as a facilitator is 90%, a slope as an obstacle is 70%, and a step as an obstacle is 0%. These confidence levels may have different values for another PWMD as a function his/her own personal capabilities, experiences, and skills. $SaliencyF_k$ and $SaliencyO_k$ are the layers that indicate the visual saliency of facilitators and obstacles. $VisibilityF_k$ and $VisibilityO_k$ are the visibility layers of facilitators and obstacles.

$$A_2= Normalize\left(SaliencyF_k\_layer\right)*Normalize(VisibilityF_k\_layer) \tag{3.18}$$

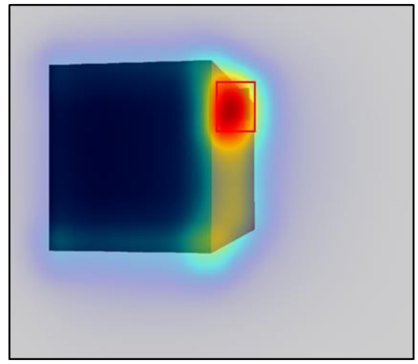
$$A_3= Inverse\_Normalize\left(SaliencyO_k\_layer\right)*Inverse\_Normalize(VisibilityO_k\_layer) \tag{3.19}$$

$$L_4= Normalize(A_1+A_2+A_3) \tag{3.20}$$

where A_2 and A_3 denote the level of accessibility of facilitators and obstacles, respectively. L_4 is the normalized level of accessibility as the fourth legibility factor that is calculated by the sum of the accessibility levels in the presence of facilitators (scenes and objects) and obstacles.



(a)



(b)

Figure 3.9: A frame in which (a) an object is extracted and (b) the saliency of the object is determined.

Finally, all generated layers are normalized for the different factor scales, and afterward combined. The combination of visibility, connectivity, complexity, and level of accessibility after normalization is conducted using a weighted sum function. This final layer indicates the legibility value of the indoor environment based on the capabilities of the PWMD.

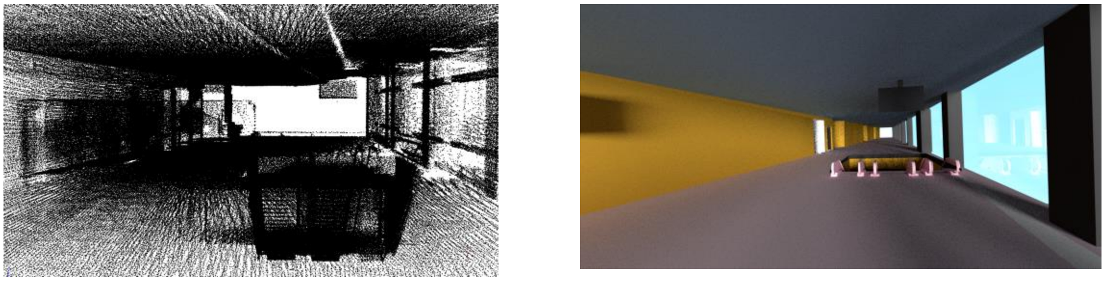
$$Legibility = \sum_i^n W_i L_i \tag{3.21}$$

where L_i denotes a layer of legibility factor and W_i is the significance weight associated with this legibility factor. The sum of weights in this equation is equal to one. For the implementation in the next section, we consider equal weights for these factors.

3.7. Case Study

To illustrate and evaluate the proposed approach for legibility assessment, the Quebec City Convention Centre was used as a case study. The Convention Centre is one of the largest buildings in the old city, with several floors connected via numerous stairs and elevators. It also links two large hotels and houses several shops and restaurants, as well as a large public parking lot. Over 200 events are held annually in the center and more than 200,000 people visit it each year. This building is, for the most part, accessible to anyone using a wheelchair. According to the standards of the National Building Code of Canada and the American Disabilities Act, the Kéroul group (a non-profit organization in the province of Quebec that promotes accessible tourism) has certified the Convention Center as an accessible indoor building for PWMD.

In order to measure the building's legibility, we created a 3D model of the building. For this purpose, we collected 3D point clouds using lidar data. Figure 3.10b shows the 3D model of this building constructed from the point clouds (Figure 3.10a). For this task, a GeoSLAM laser scanner (ZEB revo model) and a built-in camera designed for collecting indoor 3D points were used. We then extracted a 3D model from the point cloud data as well as a 2D plan of the building.



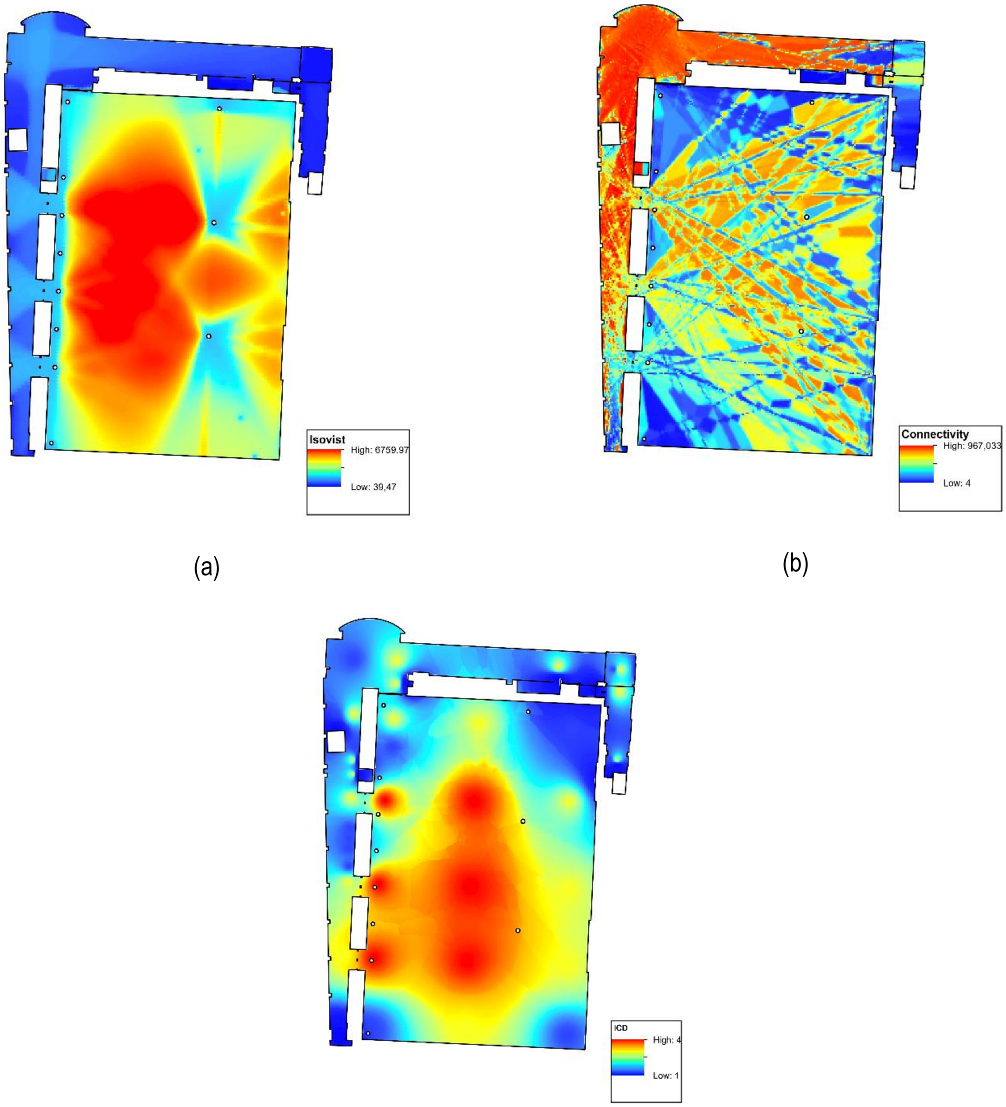
(a) (b)

Figure 3.10: A 3D model of Quebec City Convention Centre, (a) 3D point cloud, and (b) 3D model.

For the visibility calculation, the isovist tool of Depthmap software (Turner, 2004) was used. To achieve this, floor spaces were divided into a grid. From each cell within the grid, the visibility level was determined and the results were saved as a raster layer. Figure 3.11a shows the output visibility layer. The places with high visibility are considered to be more legible compared to other cells.

The level of connectivity suggested by O'Neill (1991) was also applied to model this component of legibility. This factor was calculated based on the axial map method. For this, we used Depthmap software to create a layer with multiple axial lines on the building floor. Every line was then given a numeric label determined by the number of connections with other axial lines. Inside the building, on the fourth floor, the maximum number of connections was calculated as 967, and the minimum was four connections (Figure 3.11b).

The ICD was another factor used to characterize the complexity of the environmental layout based on the navigational graph created for the building's fourth floor (Figure 3.11c). ICD values were estimated as 4, 3, 2, and 1 for the structure of this building. The average ICD for this floor was computed as 2.7, demonstrating a moderately high level of complexity for the building.

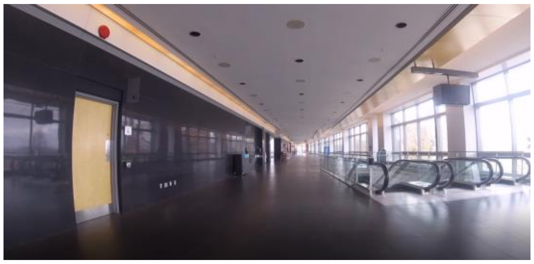


(a) (b)

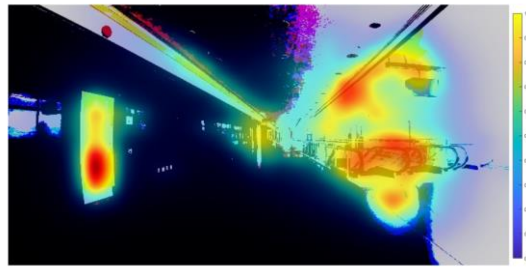
(c)

Figure 3.11: Legibility factors including (a) isovist, (b) connectivity, and (c) ICD.

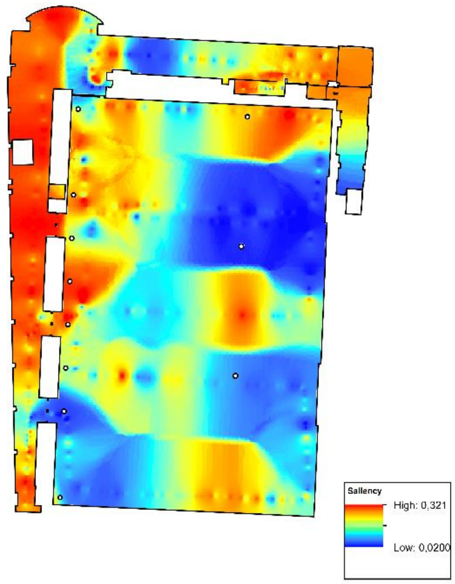
To estimate the level of accessibility from facilitators in the scenes in our study area, we determined the visual saliency of geo-tagged video frames obtained inside the building using the GBVS algorithm (Sharma, 2015) in terms of color, ambient light intensity, orientation, and contrast (Figure 3.12b shows the visual saliency of one frame (Figure 3.12a) captured inside the Convention Centre). Following this, we interpolated the saliency data to create a layer based on the color and intensity of the light, the orientation of entities and their contrast with neighboring areas. Figure 3.12c illustrates the results of the interpolation of the saliency data of each frame of the geo-tagged video. To better take into consideration the visibility constraints of PWMD, we captured the geo-tagged video from a wheelchair's height.



(a)



(b)



(c)

Figure 3.12: Mapping of saliency of scenes, (a) a frame of a geo-tagged video for a given wheelchair's height, (b) its saliency map, and (c) the saliency of the whole area.

In order to measure the effect of obstacles and facilitators (objects) on the environment for assessing the level of accessibility, we incorporated their visibility and visual saliency assessments from the geo-tagged video frames. As previously mentioned in the conceptual framework section, we classified obstacles and facilitators in the building according to the method proposed by Park et al. (2020), that is, into: (1) monitors (dynamic signs to aid navigation as facilitators), (2) stairs (obstacles), (3) elevators (facilitators), and (4) escalators (obstacles). A person's confidence level when moving in the presence of each aforementioned object was assumed to vary between 0 and 100%. Then, in order to calculate the accessibility level of these obstacles and facilitators, the visibility of each class in each frame was calculated based on the ratio of the number of pixels of that class to the total number of pixels of the frame. Additionally, the saliency of each class in each frame was determined by measuring the visual saliency of the class pixels using the GBVS method. The accessibility level of a class in the frame was calculated by multiplying the visibility and the visual saliency. Figure 3.13 shows the visibility of monitor 2 inside the building. Additionally, this figure shows that the closer one gets to monitor 2, the greater the probability of viewing the monitor. However, the maximum visual saliency is in a place far from the monitor. The accessibility level indicates that the location near the monitor is the most affected, which is not in the highest visibility area near the monitor.

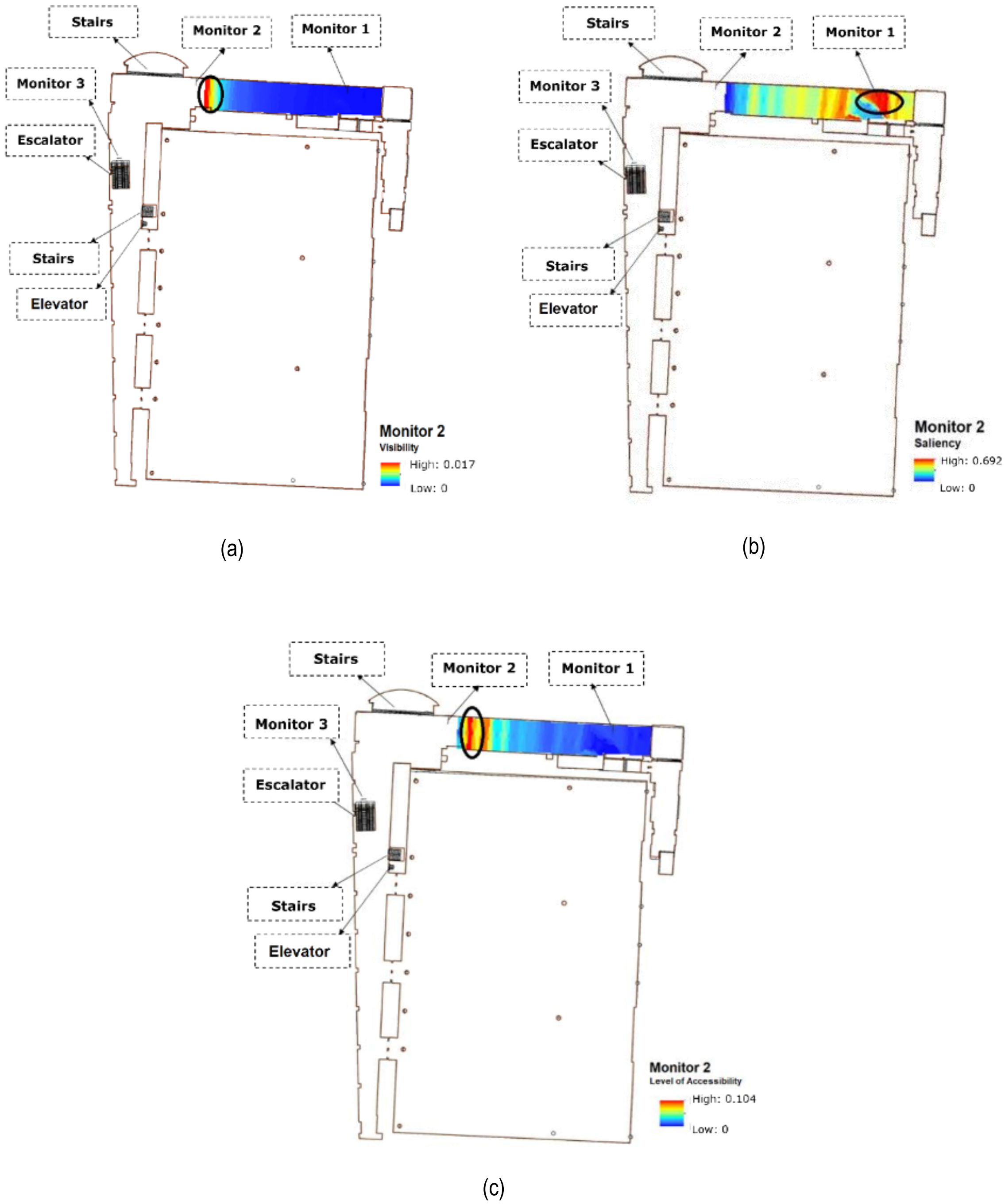


Figure 3.13: (a) Visibility, (b) visual saliency, and (c) accessibility level of monitor 2.

This process was conducted in order to calculate the accessibility level of other obstacles and facilitators from the point of view of a PWMD. Finally, these levels of accessibility of the environment were measured by overlaying the accessibility level of all obstacles and all facilitators. Figure 3.14 shows that the lowest of accessibility occurs near the escalator. In general, these considerations will influence the legibility for PWMD. In fact, when decreasing the accessibility level, decision time is increased for people who want to find suitable and accessible paths.

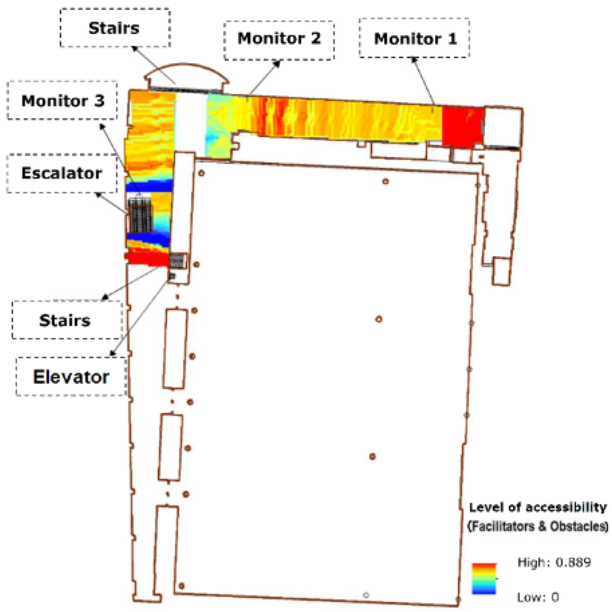


Figure 3.14: The level of accessibility for objects (facilitators/obstacles).

Finally, the legibility layer of the building was obtained by overlaying all the layers corresponding to each factor based on our proposed estimation approach (Figure 3.15). Figure 3.15 shows that the corners of the main hall on the fourth floor of the Convention Centre building have the highest legibility (regions 5, 6, and 7 in Figure 3.15). The lowest legibility within the building's main aisles is found close to the main intersection and just before the second decision point concerning whether to choose the stairway or go straight (region 3). Additionally, the entrance (region 4) to the main hall is less legible than other parts of the building. This final estimated legibility value is better adapted to the needs of PWMD, because (1) the trajectory is generated according to the movement of a person with a motor disability, (2) the geo-tagged video is recorded on the trajectory of a person with a motor disability (with consideration of his/her wheelchair's height), and (3) facilitators (e.g., elevators) and obstacles (e.g., stairs) are extracted based on the PWMD's capabilities.

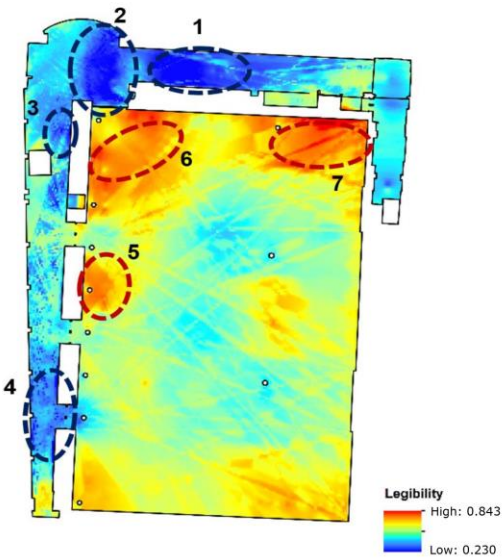
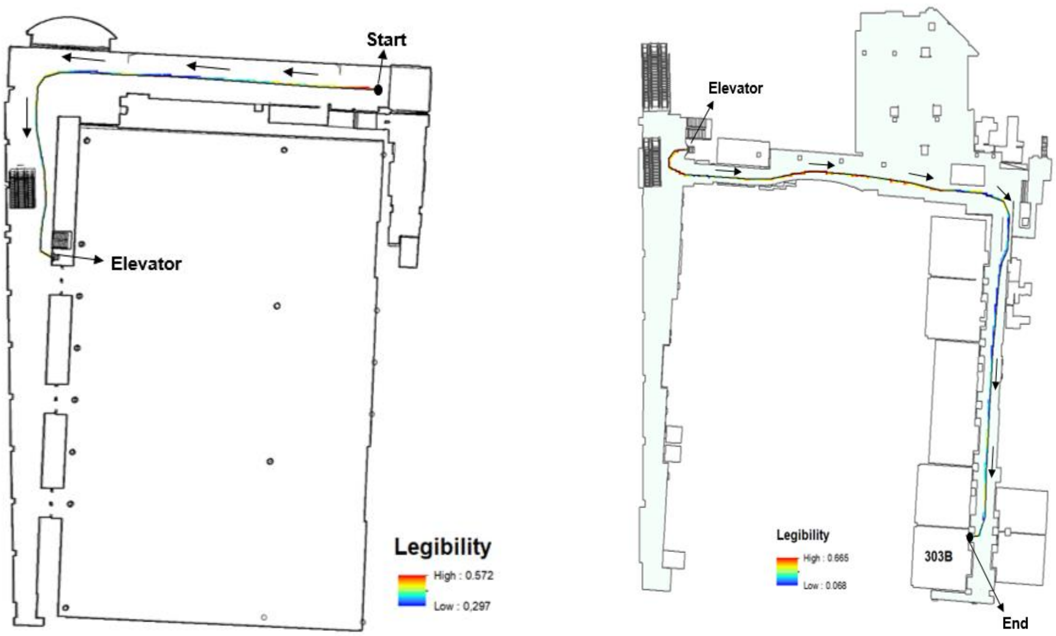


Figure 3.15: Calculated legibility.

As a scenario, in order to calculate the legibility of a trajectory for PWMD for a particular location inside the Convention Centre building, we studied a sample trajectory from the 4th floor (the ground floor) to the 3rd floor (one level below the ground floor). The output of this step is based on our proposed method for legibility assessment that determined the level of legibility for each segment of this trajectory. Figure 3.16 shows the path legibility using different colors from blue (low legibility) to red (high legibility).



(a) (b)

Figure 3.16: Legibility of a trajectory of a person using a wheelchair from (a) floor 4 to (b) floor 3.

This color-coded, segmented trajectory based on the calculation of legibility could be applied to develop a path planning strategy for navigation applications. In addition, the result could likewise be utilized to create a smart environment to guide people during their mobility tasks and to avoid areas that pose difficulties (low legibility in this case) or provide them with relevant information to ensure their security during their navigation tasks. Furthermore, the legibility calculation could be adjusted for different disability profiles. Hence, we propose to use this output for developing an adaptive method for optimizing sensor placement to improve the navigation guidance, especially in the places where legibility is low (Afghantoloee & Mostafavi, 2018).

3.8. Discussion

In this paper, we have proposed a novel framework for the assessment of the personalized legibility of indoor environments based on the Disability Creation Process (DCP) model. We argued that the legibility of an environment is the result of the interactions between personal factors and environmental factors, highlighting the importance of the consideration of personal perceptions, capabilities, experiences and skills in the evaluation of the legibility of an indoor environment. This has been done with the aim of designing smarter and more accessible indoor environments, leveraging the potential of advanced navigation and communication technologies to help PWMD in their mobility.

In the proposed model, we have considered different factors affecting the legibility of indoor environments, starting with factors such as visual access, connectivity, and complexity of building layout and extending the concept to include the accessibility level as one of the most important factors in the evaluation of the legibility of an environment, especially for PWMD. We argued that the level of the legibility of the environment should be personalized as a function of the perceptions, capabilities, and experiences of each individual, which are different. Although the difference in legibility level for the general population may not be significant, however, depending on the severity and type of disability, the difference of legibility may be very significant for PWMD.

In line with the personalization process, we argued that all of the factors, such as visual access, connectivity, and complexity, result from the interactions of humans with their environments. However, in previous research, they are often estimated based solely on the geometric characteristics of the environment and are rarely personalized for the legibility assessment. In addition, we found that legibility can be explicitly linked with accessibility level. We argued that the measurement of the visual saliency and visibility of facilitators and obstacles are key elements that should precede the accessibility assessment. Indeed, these objects should first be perceived by people in order to determine their legibility, especially in an unfamiliar environment. In terms of accessibility, we have reported that for PWMD, obstacles contribute to an increase in the risk of falling or accidents during a mobility task. Hence, the presence of obstacles decreases the legibility of the environment, whereas the perception of facilitators helps to increase the legibility of the environment. Considering these elements in the development of assistive navigation technologies would help to personalize routes and instructions for PWMD. It is worth mentioning that the concepts of obstacles and facilitators are not absolute, and an object can be an obstacle for one individual but be considered a facilitator for others. This needs further investigation so that the environment can be adapted to accommodate different needs in a more optimal approach.

In our experiment, and for the sake of simplicity, we made several assumptions to produce the results presented. For instance, we computed more generic legibility values for the whole population with and without disabilities that need to be further specified in future experimentation for specific PWMD. In addition, for the purpose of this paper, we did not define specific weights for each factor based on significance. In fact, our results in the case study were obtained with the assumption that the weights of the proposed legibility factors were equal. However, the importance of the legibility factors can be changed according to an individual's profile. Hence, in order to specifically determine the weight of each legibility factor, it is necessary to evaluate the mobility performance of PWMD (with different profiles) in the environment. This will be further investigated in the next stage of our research.

Finally, the proposed model needs further validation effort. An alternative option for the validation of the legibility layer would be to carry out an experiment with the participation of a group of PWMD as well as a group of people without disabilities for comparison purposes. According to Li and Klippel (2016), by recruiting people, in this case PWMD, we may measure the ability of these people to reach their destination by assessing indicators such as the number of mistakes to reach their destinations, the time taken and the additional distance traveled with respect to the shortest path from origin to destination. With these indicators, we can correlate the calculated legibility layer with the mobility performance of PWMD. In addition, we may estimate the significance of the legibility factors using these indicators.

3.9. Conclusions and Future Work

In this paper, we proposed a novel conceptual framework for the assessment of the personalized legibility of indoor environments for PWMD. First, the legibility was conceptualized as the result of interactions between a person with motor disability and the environment, based on the Disability Creation Process model proposed by Fougeyrollas et al. (2019) and also drawing upon affordance theory. We argued that the personalized legibility of the environment results from the perception of the environment by each individual and depends on the mental representation that the person has of the environment. We also argued that this mental representation is enriched according to the sense–plan–act paradigm for each person. Legibility concerns how easily this map is understood and how well it supports the mobility of PWMD in an indoor environment.

We argued that legibility is affected by several factors derived from the integration of personal and environmental factors for a specific task. We proposed factors including physical characteristics of the environment and the consideration of obstacles and facilitators, which affect PWMD more significantly than the general population, but will also impact the latter. We suggested that in addition to the interconnected density or ICD, visibility, and connectivity factors, legibility is affected by the level of accessibility, including the visual saliency of scenes (e.g., color, intensity, contrast, and orientation of the visual field) and the presence of facilitators and obstacles with consideration for their visibility and visual saliency.

Based on the legibility factors and the proposed legibility estimation for PWMD, a legibility layer was calculated for the Quebec Convention Centre building, on the 4th floor. This legibility layer shows that the lowest legibility is located near the building escalator, whereas the highest legibility is located near the walls and corners of the main hall.

This approach allows architects and engineers to get a better estimation of the level of legibility and facilitates subsequent actions to increase the legibility of indoor environments, especially for PWMD. Furthermore, this approach may help to create a smart environment where sensors and actuators are optimally located to support better wayfinding. It may also help to improve navigation systems by suggesting more adapted and legible paths instead of shortest paths for PWMD.

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4. Une méthode d'optimisation locale basée sur le diagramme de Voronoi 3D pour le déploiement de réseaux de capteurs dans des environnements intérieurs complexes

4.1. Résumé

Le déploiement optimal d'un réseau de capteurs dans les environnements construits, en particulier dans les environnements intérieurs, est l'un des défis dans le domaine de la conception de réseaux de capteurs pour le traçage, la surveillance et le contrôle des phénomènes dynamiques (par exemple, les mouvements de personnes). La plupart des méthodes actuelles de déploiement et d'optimisation des réseaux de capteurs sont basées sur une approche manuelle et l'expérience des personnes responsables, ce qui n'est généralement pas optimal et entraîne des lacunes de couverture importantes dans la zone surveillée. Pour pallier ces limitations, plusieurs méthodes d'optimisation ont été proposées au cours des dernières années. Cependant, la plupart simplifient à l'excès l'environnement et ne tiennent pas compte de la complexité de la nature architecturale 3D des environnements construits spécialement pour les applications intérieures (par exemple, la navigation intérieure, l'évacuation, etc.). Dans cet article, nous proposons un nouvel algorithme d'optimisation locale basé sur un diagramme de Voronoi 3D qui permet une définition claire des relations de proximité des capteurs dans des environnements intérieurs 3D. Afin d'évaluer notre méthode, nous avons comparé nos résultats avec l'algorithme Genetic Algorithm (GA) et l'algorithme Covariance Matrix Adaptation Evolution Strategy (CMA-ES) comme méthode stochastique efficace. Les résultats montrent que la méthode proposée atteint une couverture de 98,86 %, ce qui est comparable aux algorithmes GA et CMA-ES, alors que le temps de calcul de la méthode proposée est presque six fois inférieur à celui des algorithmes GA et CMA-ES.

Corps de l'article

Titre: A local optimization method based on the 3D Voronoi diagram for sensor network deployment in complex indoor environments

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4.2. Abstract

Optimal sensor network deployment in built environments for tracking, surveillance, and monitoring of dynamic phenomena is one of the most challenging issues in sensor network design and applications (e.g., for tracking the movement of people). Most current methods for sensor network deployment and optimization are empirical and they often result in important coverage gaps in the monitored areas. To overcome these limitations, several optimization methods have been proposed in recent years. However, most of these methods oversimplify the environment and do not consider the complexity of the 3D architectural nature of the built environments specially for indoor applications (e.g., indoor navigation, evacuation, etc.). In this paper, we propose a novel local optimization algorithm based on a 3D Voronoi diagram, which allows a clear definition of the proximity relations between sensors in indoor 3D environments. This proposed structure is integrated with an IndoorGML model to efficiently manage indoor environment components and their relations as well as the sensors in the network. To evaluate the proposed method, we compared our results with the Genetic Algorithm (GA) and the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) algorithm. The results show that the proposed method achieved 98.86% coverage which is comparable to the GA and CMA-ES algorithms, while also being about six times more efficient.

Keywords: Deployment, sensor network, indoor, 3D environment, 3D Voronoi structure

4.3. Introduction

Advances in sensor technologies increasingly allow efficient and on-the-fly tracking and monitoring of diverse dynamic phenomena for different applications. These applications may include disaster management, traffic management, security surveillance, flood monitoring, and real-time tracking for mobility applications (Arampatzis et al., 2005). For the efficient tracking and monitoring of dynamic phenomena using a sensor network, different issues related to sensor types, sensing models, connectivity, communication, location and coverage as well as efficient assessment of real-time measurements need to be addressed.

Among these issues, optimal sensor placement is a prerequisite for efficient monitoring and coverage in a given environment. Traditional methods for sensor network deployment are mostly experimental and not efficient. Other optimization approaches are rarely context-aware and they do not consider the complexity of the environment (Cortes et al., 2004; Huang & Tseng, 2005; Wang et al., 2006; Zou & Chakrabarty, 2003). In addition, these methods usually oversimplify sensor models (sensing fields). This is especially true for the built indoor and outdoor environments where the presence of diverse features such as buildings, walls, trees, floors, and stairs complexify not only the communication between sensors but also their placement and optimization. In recent years, there have been some efforts to improve sensor models and hence increase the quality of measurements obtained from a sensor network. For instance, in (Konda & Conci, 2013), the deployment of wireless cameras was carried out by considering the quality of images related to light resources, distortion phenomena in cameras, and coverage area, as well as a constraint regarding connectivity between cameras in indoor environments. However, several problems regarding the optimal deployment of sensor networks in indoor environments remain. In fact, the existing optimization methods for sensor network deployment and optimization do not consider the complexity of 3D environments and their architectural design. It is also very challenging to consider the presence of diverse obstacles in such environments within the optimization process.

Most existing research for sensor network optimization is based on stochastic approaches which are generally time-consuming and inefficient. In contrast to stochastic approaches, approaches based on local optimization methods, Virtual Force (Zou & Chakrabarty, 2003), and the Voronoi diagram (Wang et al., 2006) have demonstrated a better performance in this regard. Virtual Force approaches have a high number of parameters allowing the algorithm to remain in the local optima, whereas the Voronoi diagram is a spatial partitioning method that helps to efficiently manage the proximity information between objects (sensors) with minimal setting parameters (Hashemi et al., 2011). Despite the aforementioned advantages, however, there has been a paucity of efforts (Akbarzadeh et al., 2013; Argany et al., 2012; Cortes et al., 2004) based on these approaches for sensor placement in an indoor 3D environment.

Hence, in this paper, we propose a 3D Voronoi-based optimization method for sensor network deployment in complex indoor environments (e.g., omni-directional cameras). The proposed method benefits from the combination of a 3D Voronoi diagram with the 3D vector environment model (IndoorGML) to efficiently manage both the indoor environment and its components as well as the spatial distribution and relations between sensors in the network. To illustrate the validity of the proposed method, three experiments were conducted. The first experiment was designed to evaluate the efficiency of our proposed algorithm for the placement of four omni-directional cameras with unlimited sensing ranges. Following this, the sensitivity of the proposed method was examined for cameras with more, limited sensing range and different numbers of cameras in the second and third experiments.

The remainder of this paper is organized as follows. In Section 4.4, recent studies dealing with sensor network deployment issues are reviewed. Next, in sections 4.5 and 4.6, we present our optimization methods for sensor network deployment in an indoor environment considering both the outer (environmental) and inner (sensor) factors. We then illustrate the strengths of the proposed 3D Voronoi-based approach for the deployment of a sensor network in an indoor environment, via a case study carried out in the Quebec City Convention Center presented in Section 4.7. Finally, in Section 4.8, results are compared between two stochastic optimization methods (Genetic Algorithm (GA) and Covariance Matrix Adaptation Evolution Strategy (CMA-ES)) and conclusions and future works are presented.

4.4. Related research

Optimal deployment of a sensor network to enable an indoor environment for the tracking and monitoring of its dynamics for applications such as mobility and navigation activities is a challenging task (Guvensan & Yavuz, 2011; Kivimäki et al., 2014). Coverage problems in sensor networks have been intensively studied in the last decade. Depending on the type of application, one may be interested in either target or area-based coverage. In some sensor network applications, monitoring target points such as buildings, doors, and corridors is desired, while in other applications, the aim is to track mobile targets such as intruders (Guvensan & Yavuz, 2011). Hence, covering the maximum number of target points, instead of a whole area, is the main objective in the target-based coverage problem (Kumar et al., 2004). However, the presence of obstacles may complicate monitoring tasks and the achievement of such a goal (Li et al., 2003). To overcome these limitations, efforts have been made based on visibility graphs to consider how the presence of obstacles affects the computation of a best coverage path between sensors and targets (Roy et al., 2007).

In the area-based coverage problem, which is the focus of this paper, the objective is to maximize the area covered by sensors. The quality of the coverage is expressed by the ratio of the covered area to the whole area (Huang & Tseng, 2005). Area-based coverage calculation methods are subdivided into: (1) raster-based methods (Akbarzadeh et al., 2013; Argany et al., 2012; Cortes et al., 2004), which are limited by the spatial resolution; and (2) vector-based models (Ghosh & Das, 2006; Guvensan & Yavuz, 2011; Ma et al., 2009; Wang et al., 2006; Wang & Cao, 2011). These methods have been mostly applied for 2D coverage of spaces and rarely consider the presence of man-made objects in the 3D environment.

In recent years, several methods (e.g., global or local, deterministic or stochastic) have been proposed to optimize the configuration of sensors in a sensor network based on maximum coverage criteria (Akbarzadeh et al., 2011). The Genetic Algorithm (GA) (Romoozi & Ebrahimpour-Komleh, 2012), Particle Swarm Optimization algorithm (PSO) (Kulkarni & Venayagamoorthy, 2011), Simulated Annealing (SA) (Niewiadomska-Szynkiewicz & Marks, 2009), and Covariance Matrix Adaptation Evolution Strategy (CMA-ES) (Akbarzadeh et al., 2011) are examples of global optimization methods. In these methods, an objective function for the whole network reconfiguration is adopted, whereas in local algorithms such as Virtual force-based (Zou & Chakrabarty, 2003), VECtor-based, and Voronoi diagram-based algorithms (Wang et al., 2006), reconfiguration of sensors is done with respect to the presence of neighboring sensors and the local environmental context.

Global algorithms have been used for globally optimizing the configuration of sensor networks. In these methods, for each optimization step, the cost function for the solution must be estimated for the computation of the next generation of solutions. For instance, in the GA algorithm, the cost function must be calculated for 100 solutions in each iteration; if the number of iterations is 100, the number of cost function calculations is 10,000. If the duration of the calculation of the cost function is 3 s, the total time becomes 30,000 s. Hence, global algorithms are time-consuming due to the high number of cost function (e.g., coverage) computations for sensor network optimization.

In contrast, in most of the local optimization algorithms, no cost function is used to define the movement strategy of sensors within a network (Argany, 2015). Indeed, these algorithms attempt to maximize the network coverage according to the local spatial information for the environment as well as the information related to the configuration of the neighboring sensors. For instance, in Yaagoubi et al. (2015), a Voronoi-based algorithm is used for the deployment of a set of cameras by considering the information on the structure of the environment. Their results showed that the optimal placement for cameras were close to the edges of the Voronoi cells. In general, although these algorithms are fast and do not need to recalculate the cost function as in global approaches, they have limitations in terms of the consideration of constraints (e.g., managing non-deployable spaces), consideration of multi-objective optimization goals, and the need to include complex sensing models for the sensors.

One of the key issues of all sensor deployment optimization algorithms is the accurate estimation of an individual sensor coverage in a sensor network. The sensing model of a sensor may be binary or probabilistic, omni-directional, or directional. The development of precise sensing models has a significant impact on the quality of coverage estimation for a sensor network. Most of the sensor coverage estimation methods use a raster representation of the environment for optimization purposes (Akbarzadeh et al., 2013), which limits their precision and efficiency. This is because raster representations are constrained by their spatial resolution, and their regular shapes result in redundant data for unoccupied areas (i.e., the unoccupied pixels are considered in the storage volume of the raster data). Moreover, raster-based 2D models cannot be used for indoor environments to represent solid objects and columns. To overcome these limitations, in Afghantoloee et al. (2014), a sensor coverage estimation method was proposed based on a precise 3D vector-based representation of the environment.

In addition to raster and vector representations, the voxel representation of the environment has been proposed for the deployment of a camera network to track a 3D environment (De Rainville et al. 2014). Each voxel value shows the presence or absence of an object in the space. The maximum visibility of cameras was achieved by a cooperative algorithm which splits the problem into several sub-problems (Potter & De Jong, 2000). Although the voxel representation offers potential for modelling solid objects and is appropriate for indoor environments, the visibility estimation is sensitive to the resolution of the voxels.

Concerning indoor versus outdoor environments in the sensor deployment problem, the majority of research efforts have been focused on outdoor environments, and only a few research projects have considered indoor environments for sensor deployment (Konda & Conci, 2013). For example, in Konda and Conci's (2013) project, a set of cameras were deployed using a Genetic Algorithm as a global optimization algorithm to achieve maximal coverage with high-quality image output while taking into account both the availability of light and the presence of obstacles in the indoor environment. Furthermore, a "greedy" sensor deployment optimization was applied to the ceilings of a building (in a simulation case) for monitoring the indoor area (Kouakou et al., 2012). In this study, virtual obstacles were considered in the simulation and the floor surfaces were chosen as the coverage area.

In summary, most of these methods oversimplify the sensing models for each sensor (circle or spherical in the best case), as well as the environment itself (often treated as 2D, and without obstacles). Additionally, the majority of this research was developed for outdoor environments, and only a few initiatives focused on sensor deployment in indoor environments (Konda & Conci, 2013). To address these challenges, we propose a 3D Voronoi-based optimization method for sensor network deployment in 3D complex indoor environments. This method is presented in the following sections.

4.5. Methodology

In recent years, several strategies have been developed for the local optimization of sensor networks based on the Voronoi structure, which has demonstrated its potential especially for the efficient management of neighborhood information in sensor networks. For example, Argany et al. (2015) proposed a local optimization algorithm based on a 2D Voronoi diagram where each sensor was moved towards the farthest vertex of its cell iteratively to fill coverage holes in a sensor network in an outdoor environment. Doodman et al. (2014) proposed a Voronoi diagram-based approach to define a movement strategy for sensors by keeping them away from obstacles in the environment. These initiatives demonstrated higher performance in the optimization process compared to global optimization algorithms.

Given these advantages, we propose a local context-aware optimization algorithm based on 3D Voronoi diagrams for the deployment of a sensor network in an indoor environment. In the proposed method, a 3D Voronoi diagram is used for the representation of sensor positions and their topological relations within the network. A 3D Voronoi diagram also provides the necessary spatial structure for the manipulation and management of the sensors' positions and their movement for optimization purposes. A 3D Voronoi diagram, for a set of points, partitions a 3D space into polyhedral convex volumes called 3D Voronoi cells (Figure 4.1).

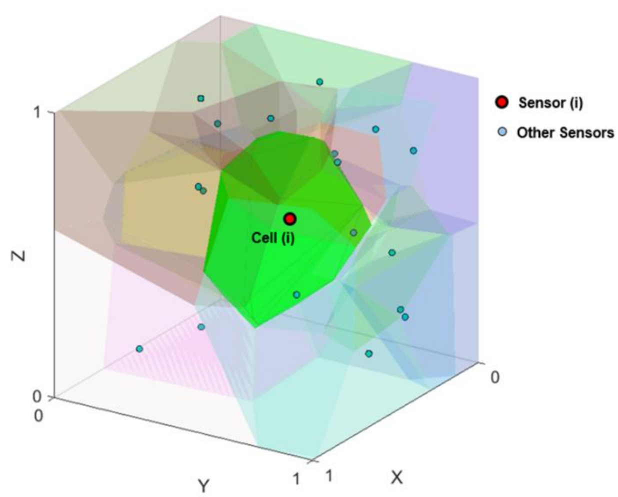


Figure 4.1: Voronoi diagram for sensor networks in 3D space.

A 3D Voronoi cell is calculated based upon the following definition:

$$VC_i=\{p_i \in R{:}d\left(p_i,S_i\right)<d\left(p_i,S_n\right)\} \quad (4.1)$$

where, S_i and S_n are the positions of sensor i and any other sensor n, respectively. VC_i is a 3D Voronoi cell, p_i is any point inside a VC_i in 3D space R, and d is the distance between p_i and any sensor S_i.

For integrating context information in the optimization process for a sensor network represented with a 3D Voronoi diagram, we incorporated the 3D IndoorGML data model proposed by the OGC. 3D IndoorGML is an extension of CityGML (level of detail 4) that provides semantic, topological, and spatial information of objects and services (OGC, 2014). IndoorGML is an open standardized data model of the interior space of 3D buildings and is composed of a core module, an appearance module, and a thematic module (Li et al., 2019). The main structure of IndoorGML divides an indoor space into multi-spaces called cells. The intersection area of two neighboring cells is called a boundary surface (Li et al., 2019). IndoorGML uses two dual spaces to model indoor environments: (1) a primal space, the geometric representation of a cell space and a cell boundary space; and (2) a dual space, the Node Relationship Graph representation of cells and their boundary surfaces, which respectively correspond to nodes and edges (Figure 4.2). IndoorGML is extended with a navigation core module that has two classes, namely, navigable space and non-navigable space. The non-navigable space represents the cells occupied by obstacles and walls. The navigable space includes all the connection spaces (e.g., doors), anchor spaces (e.g., building exits), general spaces (e.g., rooms), and transition spaces (e.g., corridors). 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 a closure surface) (Gröger et al., 2012). IndoorGML has an external reference that enables engines and data interpreters to link with CityGML to access the semantic information tagged to the surfaces.

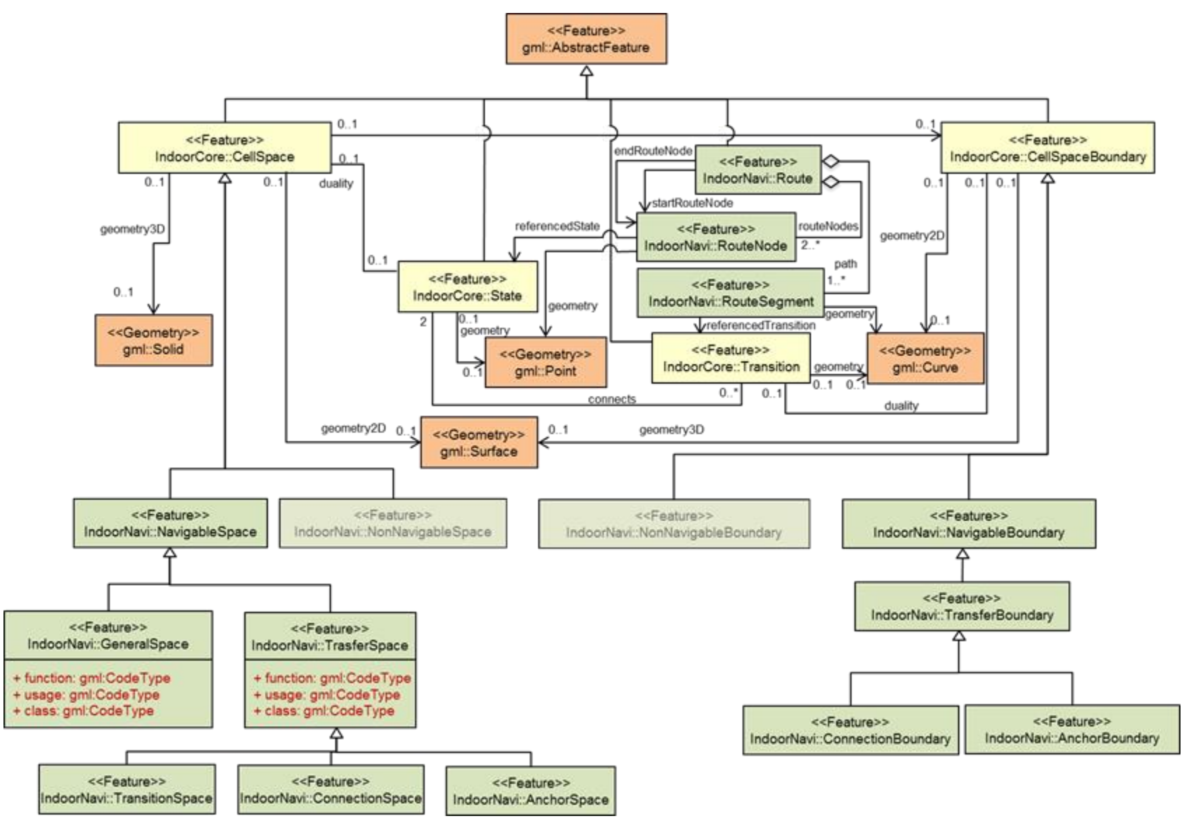


Figure 4.2: UML diagram of IndoorGML core module and navigation module (OGC, 2014).

Hence, we propose an integrated model for optimal sensor placement in an indoor environment that combines IndoorGML classes to represent indoor environments and a 3D Voronoi diagram for the representation of sensor positions and their proximity relations. The optimization algorithm uses the information of the indoor environment represented by IndoorGML and the neighborhood relations of sensors defined by a 3D Voronoi diagram. The optimization module includes our iterative local optimization algorithm. The information provided by the first two components will allow us to estimate, at each iteration, the total coverage provided by the sensor network and decide on the changes in the network in subsequent steps (i.e., individual sensor movement) to improve the network total coverage.

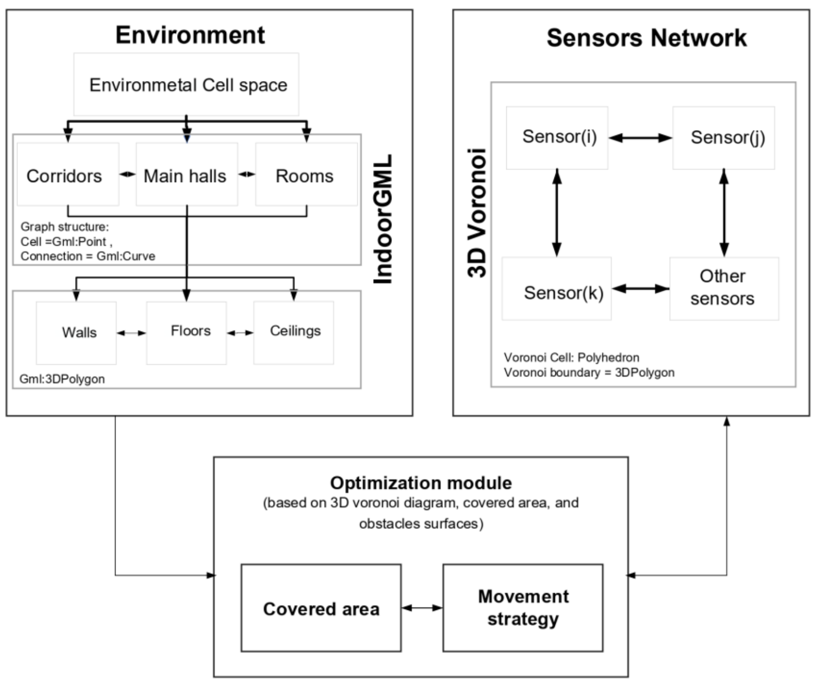
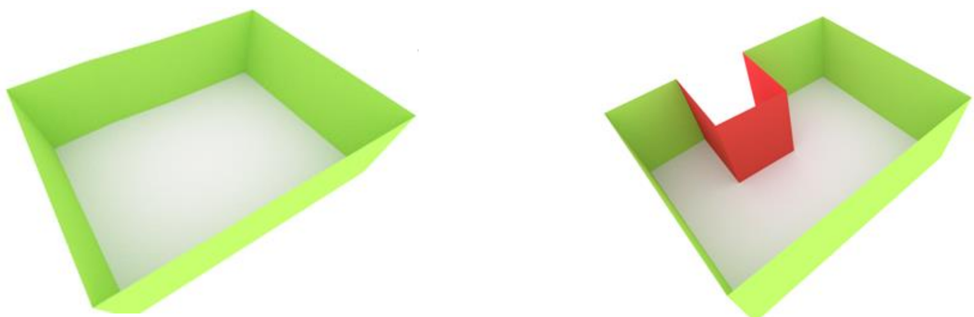


Figure 4.3: The proposed sensors deployment approach in a 3D indoor environment based on IndoorGML and a 3D Voronoi diagram.

In the proposed integrated model, the 3D Voronoi structure uses the information represented by IndoorGML to guide the optimization process. IndoorGML defines the indoor environment structures with a set of cells and stores them with their central points as nodes and with links to define the inter-cell connections. In addition, each cell is stored using a surface geometry. This structure is used as the sensor deployable space. We also tag semantic information to the cells and surfaces described by the IndoorGML model to better guide sensor placement. We use the 3D Voronoi structure together with this information to manage sensors movement and the updated proximity information between sensors. The cells in the IndoorGML model are divided into three main classes according to the priority of sensor placement. These include: (1) corridors; (2) main halls; and (3) rooms. Surfaces are also classified for each cell into four classes: ceilings; walls; floors; and obstacles. To calculate a sensor network coverage, individual sensor position and coverage change must be determined using the information provided through the IndoorGML model.

In our study, the floor surface of each cell must be covered by the sensor network. According to the sensors' positions in the Voronoi structure and considering the presence of various obstacles in the environment, the coverage estimation is calculated using a visibility approach (Afghantoloee et al., 2014). In this regard, the obstacles are defined as objects that obstruct the sensor's vision. For instance, Figure 4.4 shows the red surfaces as obstacles that reduce the covered area of sensors in a non-convex area. Sensor deployable spaces are composed of the walls and ceilings of each cell space.



(a) (b)

Figure 4.4: (a) A convex cell represented by its walls surfaces (green) and its floor surface (white). (b) A non-convex cell that includes several wall surfaces as obstacles (red).

As mentioned above, the sensor network optimization is included in the optimization module. An iterative algorithm is developed for the maximization of the sensor network coverage. At each iteration, an individual sensor is moved towards a new position that aims at improving the total sensor network coverage. This movement is based on a context-aware approach and is sensitive to the shape of the environment, the presence of obstacles in the environment as well as the presence of other sensors in the vicinity of the sensor being assessed.

As a movement strategy, each sensor is moved towards the farthest vertex of its 3D Voronoi cell by adding a repulsive force to keep the sensor away from obstacles while maintaining its position on the wall or ceiling. This strategy mainly allows one to reduce coverage overlap so as to maximize the coverage of target areas. For example, $\vec{V}_{s_1,v1}$ in Figure 4.5 shows the direction of the movement of S_1 which will allow its dispersion from other sensors. In Figure 4.5, the sensor 1 (S_1) is moved to position MS_1 in the direction of $\vec{V}_{s_1,v1}$, and is then projected onto the nearest plane (position PS_1). In the movement strategy, the sensor should be kept away from the obstacle's surfaces based on a defined distance.

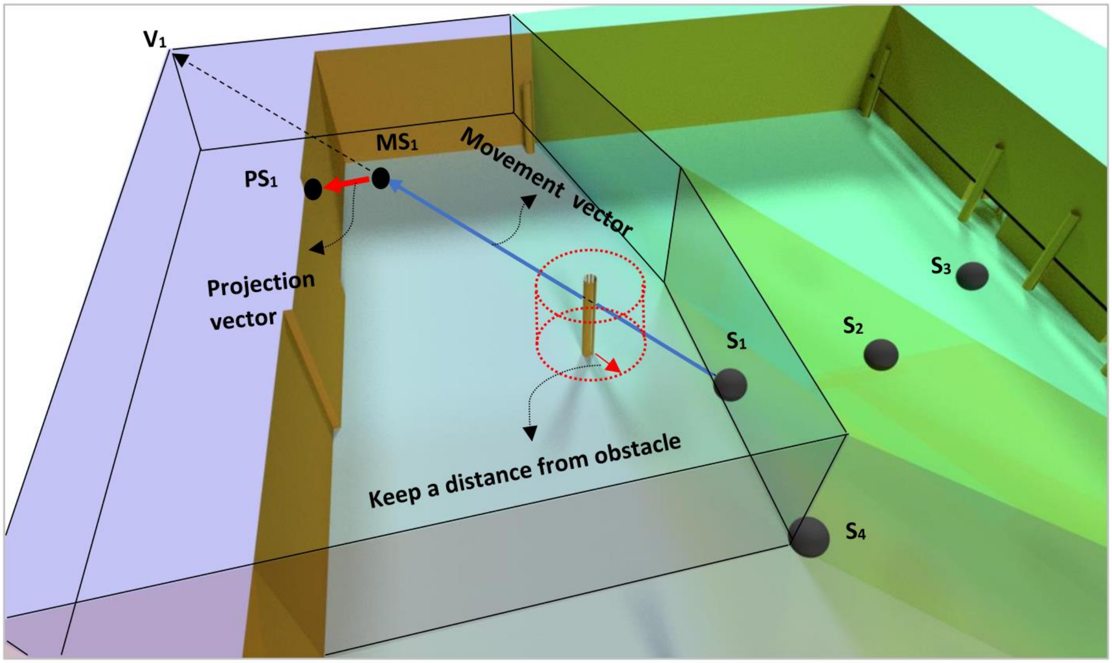


Figure 4.5: Movement strategy of sensors inside a 3D space based on a 3D Voronoi diagram (colored 3D cells) taking into account projection and obstacle avoidance.

4.6. Formal representation of the proposed optimization algorithm

In this section, we formally present the pseudo-code of our proposed local optimization method based on a 3D Voronoi diagram for sensor network deployment in complex indoor environments (Figure 4.7). In this algorithm, we assume a network of omni-directional cameras for the coverage of the indoor environment. The objective of sensor deployment is to maximize the covered areas to support applications such as indoor navigation or security purposes. We also assume that sensors can be deployed mainly on the walls and ceilings. Building floors are considered as target areas to be covered where people's activities are expected. In addition to sensor characteristics and neighborhoods, information from the 3D indoor environment is used as context information for optimal sensor network placement. The presence of other objects embedded in the indoor environment that may affect coverage information is also taken into consideration (e.g., presence of a column or other permanent obstacles such as walls).

Thus, in the proposed algorithm, first, we create a 3D Voronoi diagram using a set of generating points $(sensors\ S_1, \ldots, S_n)$. The 3D Voronoi diagram is obtained from its dual Delaunay tetrahedralization (DT) which is calculated based on an incremental construction approach (Ledoux, 2007). The incremental method for the construction of a Delaunay tetrahedralization consists of three main steps including initialization, point insertion and tetrahedralization optimization. The process starts with the definition of a universal tetrahedron large enough to enclose all the generating points (sensors) in the 3D space. Sensors are then inserted one by one in the existing tetrahedralization using a search function to find the tetrahedron that contains the newly inserted point.

Then, the tetrahedralization is locally updated to make sure that all the tetrahedrons respect the Delaunay criterion which requires that the circumsphere of each tetrahedron is empty. Indeed, the circumcentres of the final tetrahedrons are dually considered as the vertices of 3D Voronoi polyhedrons. Hence, 3D Voronoi cells are generated by connecting all the circumcentres of the neighboring tetrahedrons that share a given generating point.

In the next step, we apply an initiate coverage value (Afghantoloee et al., 2014), to each sensor in the network. The coverage value of each sensor in a 3D space is estimated based on the method proposed as follows (Afghantoloee et al., 2014). First, we eliminate the irrelevant surfaces for the computation of the coverage of each sensor. These include: (1) elimination of the back-face surfaces (e.g., surface O_2 and O_3 in Figure 4.6) in which the angle between the normal vector of a back-face surface and the sensor direction is less than 90 degrees, (2) elimination of the surfaces that lie on the back side of the sensor deployable surfaces (especially for the walls), and (3) elimination of the surfaces that lie outside the sensing distance (e.g., surface F_1). Next, we project the remaining surfaces onto a perspective plane which is defined parallel to the floor surface. We then overlay these surfaces in the projection plane (e.g., projected surface of $O_1 = F_2$ and F), in order to find the visible part of the floor (surface $F-F_2 = F_3$) covered by the sensor. Finally, we calculate the covered area by the given sensor on the floor (F_3).

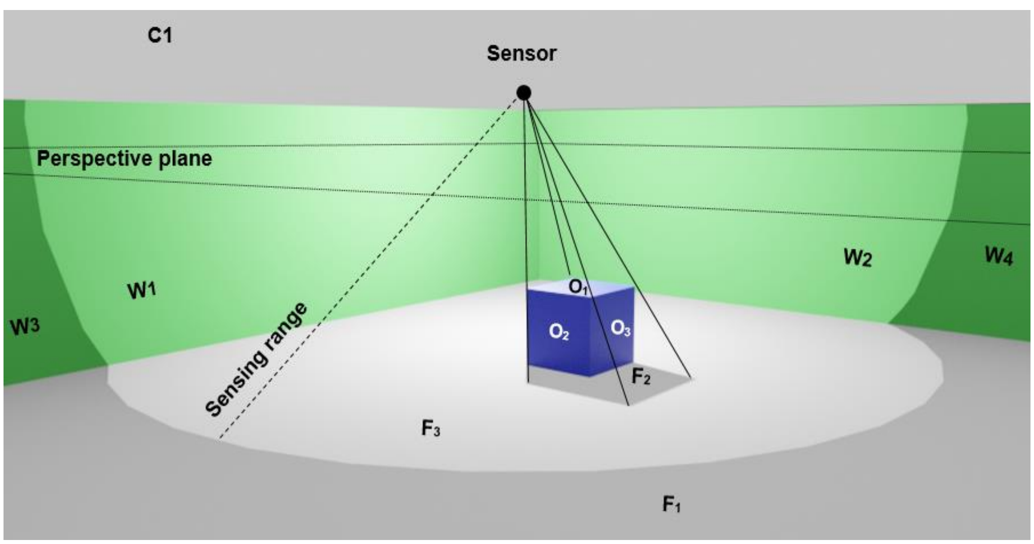


Figure 4.6: Coverage estimation based on overlapping visible surfaces projected onto the perspective plane. Surface F_1 is out of range of the sensing distance, and surface F_2 is hidden by surface O_1.

Next, we establish a priority queue (*PQ*) for the management of sensor movement (Argany, 2015). To do so, we compute the coverage gain values of the floor surfaces for each sensor based on their initial movement. The value and orientation of this movement is defined based on information about the local context as well as the sensor network configuration. The sensor movements are then organized from maximum to minimum order according to the coverage gain value (g_{si}) they produce. Hence, the first sensor in the list will be given priority to move before the others.

As mentioned earlier, the sensor movement strategy is the core element of the proposed algorithm. The strategy for a sensor *i* (S_i) to move to its new position (S'_i) is based on the neighborhood relations of the sensor defined by the 3D Voronoi diagram as well as the configuration of the environment and the presence of potential obstacles. The direction of movement is towards the farthest vertex of its Voronoi cell. The amount of movement is defined by *initial_step_size* which is 80% of the vector's length from the sensor to the farthest vertex.

input: n omni-directional cameras $S_i(x_i, y_i, z_i)$
output: (X_i, Y_i, Z_i) optimal solution
objective: Maximizing the coverage of the camera network
Initialize: Random distribution of the cameras on deployment planes
(walls/ceilings) Compute initial sensor network coverage;
3D_Voronoi(S_i,...,S_n);
step_size ← *initial_step_size;*
for *i* ← 1 **to** *n* **do**
    S'i ← *Movement strategy(S_i)*;
    {
      1- choose the farthest vertex in the same direction of path segments;
      2- amount of movement is *step_size* * vector's length;
      3- project the movement vector on the nearest sensor deployed plane;
      4- if the movement vector has an intersection with an obstacle, keep a given distance
      between sensor and obstacle;
    }
    g'_{Si} ← *coverage (S_1,...,S'_i,...,S_n)-coverage (S_1,...,S_i,...,S_n)*;
    PQ ← *add(g'_{Si},S'_i)*;
end
PQ ←*Sort(PQ, highest gain)*;
K ←*1*;
while *(*not terminated condition) **do**
    step_size ← (*initial_step_size*) ∗ (*Iteration - K*)/*Iteration*;
    S'_u ←*PQ(1).S*;
    S_u ←S'_u;
    Update_3D_Voronoi(S_i,...,S_u...,S_n);

$S'_u \leftarrow$ *Movement strategy*(S_u);

$g'_{S'u} \leftarrow$ *coverage* $(S_1,...,S'_u,...,S_n)$-*coverage* $(S_1,...,S_u,...,S_n)$;

$PQ \leftarrow$ *add*$(g'_{S'u},S'_u)$;

for $j \leftarrow 1$ **to** *N_neighboringS*$_u$ **do**

$N_{S'i} \leftarrow$ *Movement strategy*(N_{Sj});

$g'_{NSj} \leftarrow$ *coverage* $(S_1,...,N_{S'j},...,S_n)$-*coverage* $(S_1,...,N_{Sj},...,S_n)$;

$PQ \leftarrow$ *add*$(g'N_{Sj},N_{S'j})$;

end

$PQ \leftarrow$ *Sort(PQ, highest gain)*;

$K \leftarrow K + 1$;

end

Figure 4.7: Pseudo-code of the 3D Voronoi approach for sensor network optimization in an indoor environment.

Following the initialization of the 3D Voronoi data structure and the *PQ*, the iterative optimization process is defined using a while loop (Figure 4.7). In each iteration, we move the sensor on the top of the *PQ* towards the farthest vertex of its Voronoi polyhedron. It should be noted that for each sensor, the motion vector needs to be projected on the nearest deployable surface. This is needed to make sure that the sensor has a support to be installed in the 3D environment. Following this step, the selected sensor is moved towards its new position. The step size is decreased proportional to the maximum number of iterations which can be defined by the user (e.g., *Iteration* = 1000). Indeed, the step size is decreased to create a trade-off between exploration and exploitation in the search space. This ensures the avoidance of non-convergence in the optimization process (Simpkins et al., 2008).

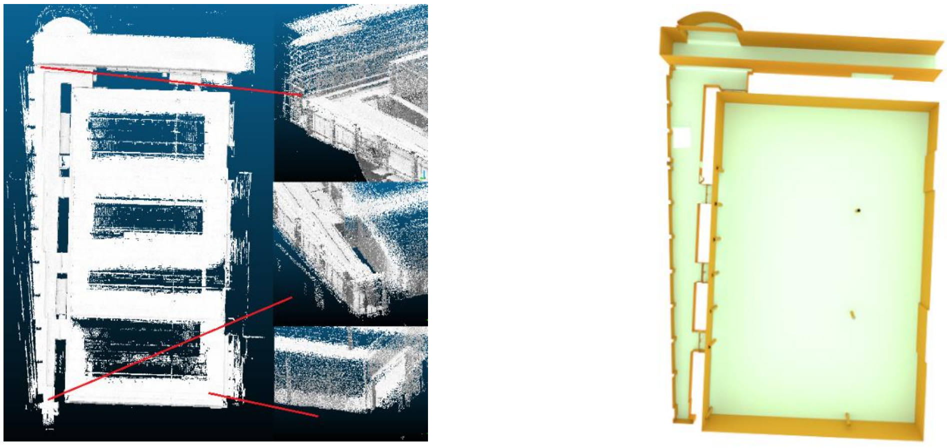
The sensor position with the highest gain coverage is updated in the while loop and the 3D Voronoi diagram is updated to reflect the new configuration of the network. The updated coverage gains for the sensor ($g'_{S'u}$) and its neighbours (g'_{NSj}) are then added to the *PQ* and sorted based on the highest coverage gain among the sensors. In the case of the presence of a permanent obstacle in the sensor movement direction, the latter needs to be kept away from the obstacle. For this purpose, we define a distance constraint to avoid the obstruction of the sensor's field of view. The while loop is terminated when the maximum coverage gain is less than a predefined coverage gain threshold (ε) for 10 iterations in a row.

4.7. Case study

4.7.1. Model of the indoor environment and sensors

For this research, the Quebec City Convention Center was selected as the study area. This building hosts many national and international events and conferences. Sensor deployment with the goal of optimal coverage inside the building is a complex task due to the complexities of its structure. This four-story building includes many conference rooms and corridors as well as several entrances, escalators, and elevators. This represents numerous cells and surfaces (walls, ceilings, floors, and obstacles) with complex architectural configurations and designs for the same floor; furthermore, the heights of the ceilings are not uniformly designed, which makes sensor deployment more difficult. Geometrically, the spaces of this building are discrete and non-convex. Traditionally, sensor deployment in such a building is carried out with a trial-and-error method, which usually results in several gaps in the network coverage. In addition, the presence of obstacles such as columns and furniture inside the building renders more difficult the deployment process and covering the gaps that result is generally neglected. Although the study area is a multi-floor building, for the sake of simplicity and feasibility we only considered the 4th floor as the test area for this study. More specifically, the study area included two main corridors and the main hall (generally used for exhibition booths, poster installations, or as a dining area for participants).

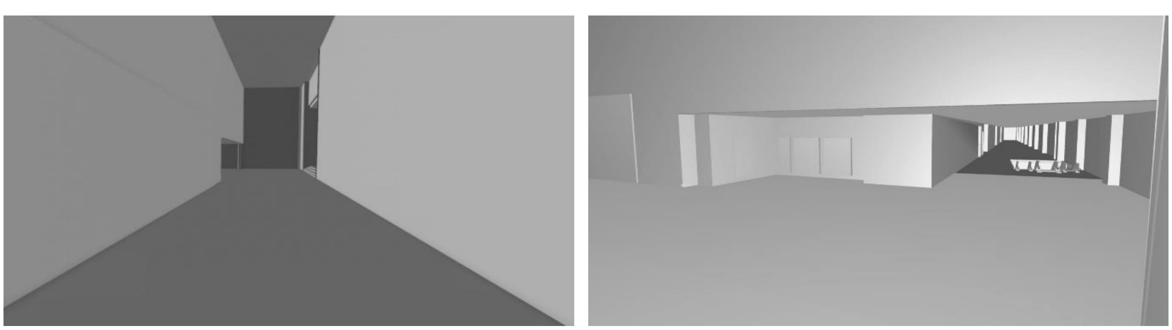
To be able to integrate the indoor 3D model of this building with our proposed deployment method, we first acquired a set of LiDAR 3D point clouds using a GeoSLAM device. This device is designed mainly for indoor environmental scanning (Figure 4.8.a). Then, we semi-automatically converted the 3D point clouds into a 3D vector model using the Blender software (Figure 4.8.b). This model was composed of a set of surfaces in a 3D space. Using the Google SketchUp software, we semantically classified the 3D surfaces into walls, ceilings, floors, and obstacles. Finally, with the IndoorGML standard, we converted the classified 3D vector model into an IndoorGML model. We then extracted the information about the 3D indoor environment from this model for our algorithm which used the cell and geometrical identifiers. Ultimately, all surfaces composing our 3D environment were extracted with their geometric information, including the coordinates of the surface boundaries, normal vectors, and semantic information such as floor numbers, cell types (e.g., corridor, hall, and room), and the type of surface (e.g., walls, ceilings, floors, and obstacles). This information helped us in defining the deployable positions for the sensors as well as for the estimation of the sensor network coverage for the environment.



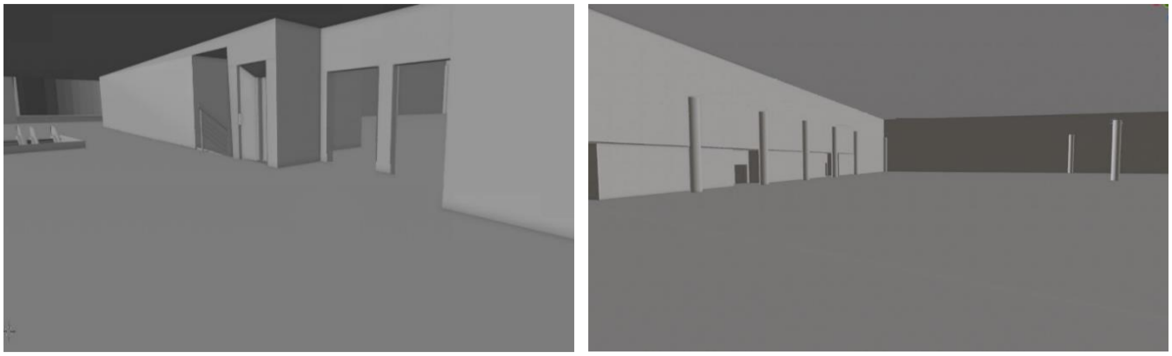
(a) (b)

Figure 4.8: The Quebec Convention Center building, (a) 3D point cloud, and (b) 3D vector model.

The 3D model of the indoor environment selected for this experiment was composed of about 1000 surface elements, including walls and ceilings on which the sensors were to be deployed. As depicted in Figure 4.9, the management of these surfaces elements as well as their topological relations in 3D space is more complex than would be the case for a simple 2D representation of the environment. Sensor deployment poses a challenge in such an environment because of the differences in the heights of ceilings and the complexities of topology between the walls and ceiling surfaces (Figure 4.9). In addition, there were many obstacles that have complicated sensor placement and the optimization processes. In our case study, the 3D environment included nine columns in the main hall. These columns were modeled as cylinders that were themselves composed of many smaller surfaces. In addition, several non-convex surface elements had to be managed inside the corridors and the main hall. These surface elements created a large search space for the computation of maximum coverage for the optimization process. Another time-consuming aspect was related to the use of the vector-based model for the computation of coverage. Vector-based coverage computation demands more computational effort than does raster-based coverage; however, it results in more accurate coverage estimation. Raster or voxel-based models may be simpler, but generally, they tend to be less accurate for coverage estimation due to their limited resolutions.



The corridor 1 The intersection space between the corridors 1 and 2



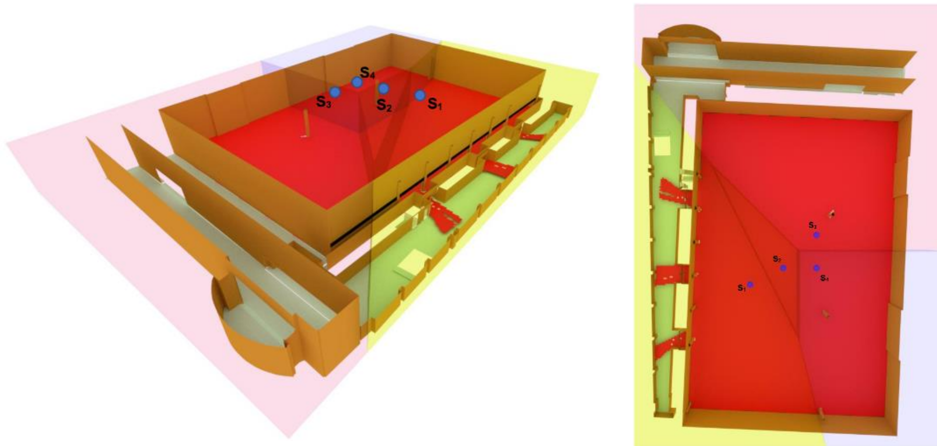
The door 1 which links the corridor 2 and the main hall The main hall

Figure 4.9: Indoor views of different spaces (corridors and the main hall) which show the complexity of surfaces in the Convention Center building.

To implement the proposed sensor placement optimization algorithm, as a first experiment, we considered omni-directional cameras without the limitation of the viewing distance and field angle. We defined the mathematical model of these cameras as a hemisphere with an infinite radius. Information in an indoor environment, such as walls and obstacles, limits the range of the sensing area and reduces the areas covered by these cameras. We selected four cameras for the deployment implementation. These cameras could only be placed on ceilings and walls (part of the walls with a height constraint from the floors were considered for facilitating camera installation). The area of interest to be covered by these cameras was considered to be on the floors. In addition, we designed two other experiments for sensitivity analysis regarding the number of sensors and sensing range. For these experiments, we increased the number of cameras and limited their sensing range.

4.7.2. Experimental results and discussions

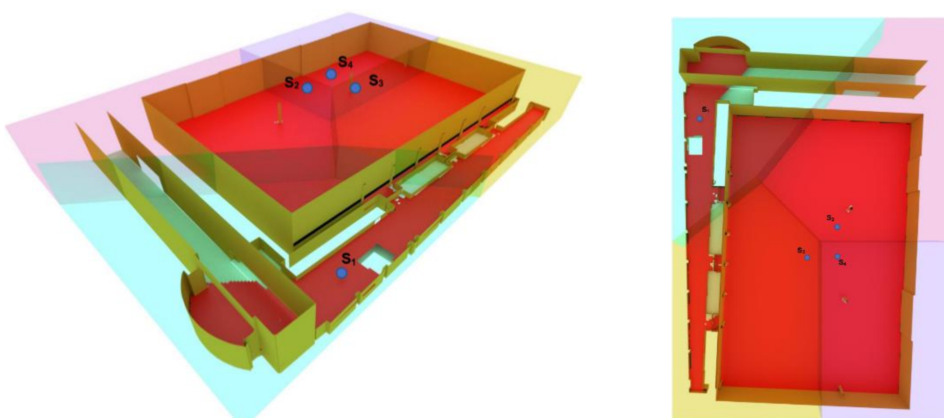
For the first experiment, the 3D Voronoi algorithm was implemented to deploy four omni-directional cameras with unlimited sensing range using the 3D vector model presented in the previous section. The deployable areas of the cameras were assumed to be on the ceiling and the walls with a distance of at least two meters from the floor. Furthermore, several columns in the main hall were considered as obstacles and their surfaces were identified in the model to consider their presence during the sensor deployment optimization process. For the initialization step, four cameras were randomly positioned on the central ceiling of the main hall (Figure 4.10).



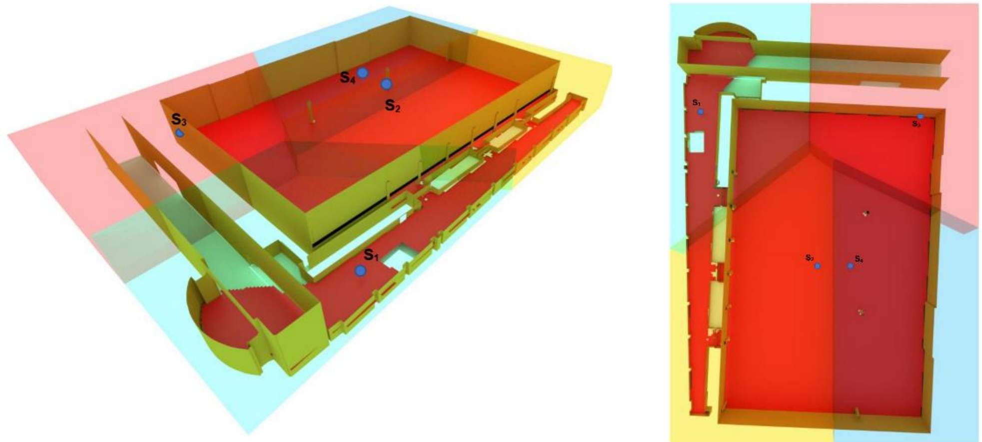
(a) (b)

Figure 4.10: Initial position of cameras in the main hall (a) side view and (b) top view.

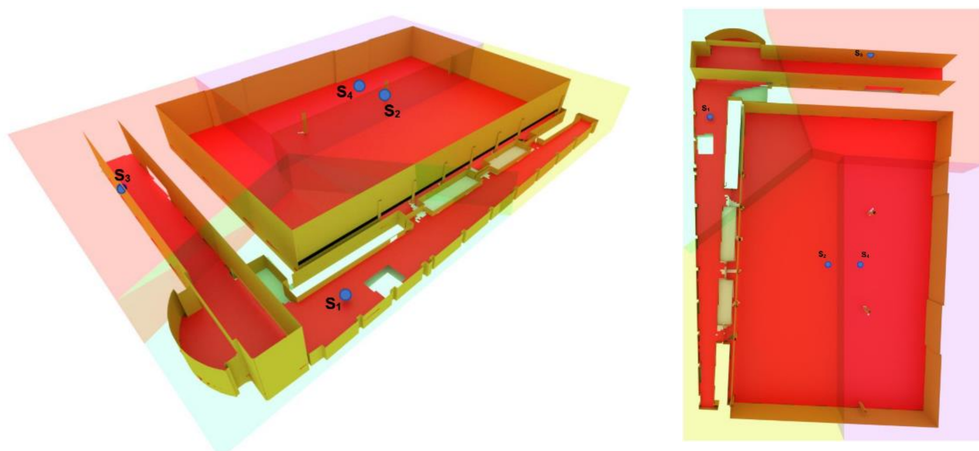
Then, at each iteration, according to the algorithm's process, the cameras moved to the farthest points of each corresponding Voronoi cell, with the projection of their locations to the nearest deployable surface. At each iteration, the camera with the most important contribution to the improvement of global coverage was chosen to be moved to its new position. Figure 4.11 shows the location of the cameras for four subsequent iterations. In this figure, the colored-transparent areas show the 3D Voronoi cells of the cameras. The red area indicates the area covered by the cameras and the blue points indicate the location of the cameras.



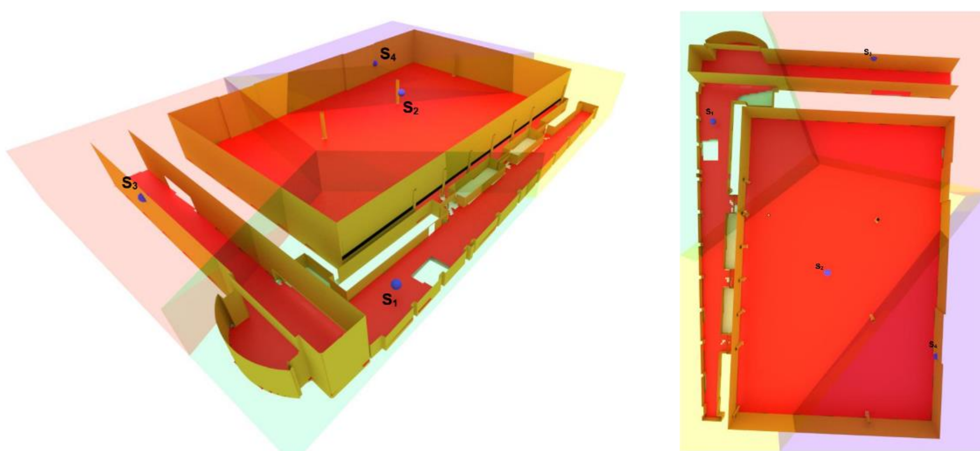
Iteration 1



Iteration 2



Iteration 3



Iteration 4

Figure 4.11: The result of the proposed 3D Voronoi approach including the positions of sensors (blue points), and their coverage (red area) for the first four iterations.

With 50 iterations, the coverage of the camera network was improved to 98% of the area. Figure 4.12 shows the convergence diagram of the 3D Voronoi approach for this case study after 50 iterations. As can be seen, the camera network coverage after 20 iterations converged on an optimal coverage. Figure 4.13 illustrates the final configuration of cameras with optimal coverage. This shows that our proposed method could deploy the sensors not only on the ceilings but also on the walls to reach the optimal coverage.

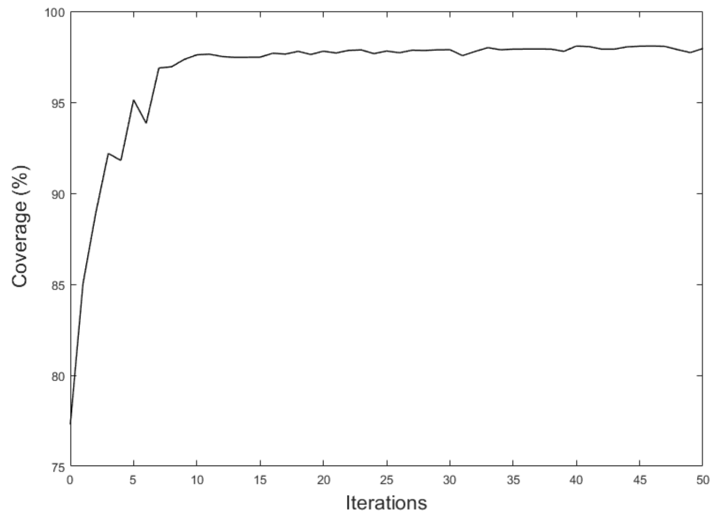


Figure 4.12: Camera coverage convergence diagram for the 3D Voronoi method over 50 iterations.

(a) (b)

Figure 4.13: Final locations of cameras obtained by the 3D Voronoi method are shown in (a) side view and (b) top view.

4.7.3. Comparison and validation

To show that our proposed algorithm reached an optimal coverage, we compared our algorithm with the Genetic Algorithm (GA) and with the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) as two examples of global methods (Argany et al., 2018). To implement the GA and CMA-ES for the deployment of the same set of cameras on the ceilings or walls, it was necessary to prepare the algorithms for the optimization process. For this purpose, we first randomly generated the initial solutions for camera configurations (solution (i) = {$X_1, X_2, X_3, X_4, Y_1, Y_2, Y_3, Y_4, Z_1, Z_2, Z_3, Z_4$}) within the 3D bounding box of the environment. Then, to achieve the deployable position of the cameras, their positions were projected on the nearest wall or ceiling surface so that we could find the right solution to calculate their coverage. In the next steps of the algorithms, the solutions were also projected on the nearby surfaces.

The initial parameters of the GA including population size, offspring percentage, and mutation percentage were selected with a trial and error method to 100%, 70%, and 20%, respectively. In addition, the setting parameters of CMA-ES are population (λ), formation of solution means, and direction (σ) that were considered as 3 + 4 × [*ln*(*n*)] (*n* = 3 × (the number of sensors)), $\lambda/2$, and 0.167, respectively.

To eliminate the random errors, the proposed 3D Voronoi method, as well as the GA and CMA-ES, were executed a hundred times. As seen in Figure 4.14, the 3D Voronoi method converged quickly to the optimal value. In addition, the final optimal coverage value of the 3D Voronoi method was greater than the coverage values of the GA and CMA-ES algorithms.

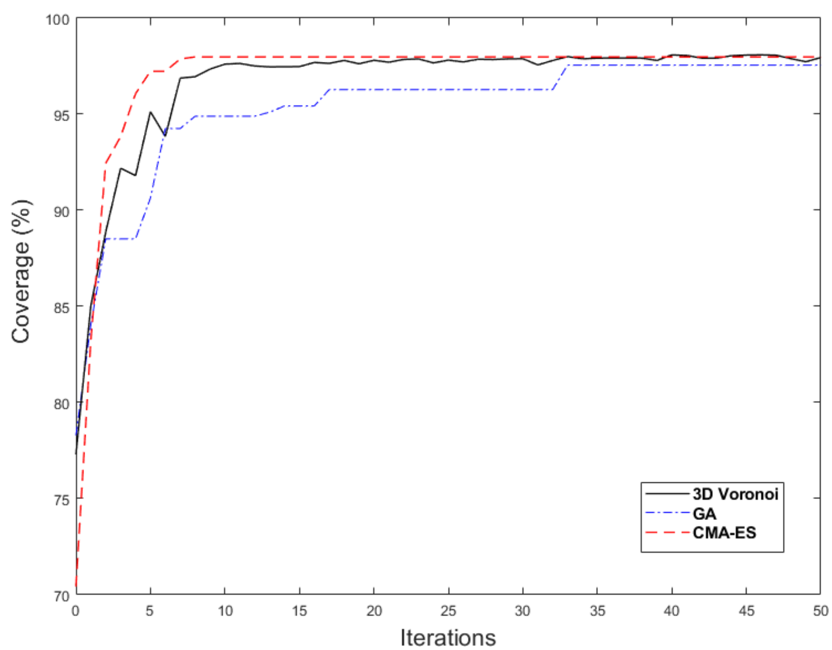


Figure 4.14: Convergence diagrams of the 3D Voronoi, GA, and CMA-ES coverage optimization methods.

According to Table 4.1, it can be concluded that the computational time of the 3D Voronoi approach was six times less than the computational time of the GA and CMA-ES algorithms. Moreover, the standard deviations reported in Table 4.1 indicate that the final coverage level of sensors in the 3D Voronoi algorithm was more robust than GA and CMA-ES algorithms. This is because our approach based on a 3D Voronoi diagram is more sensitive to the spatial information from the environment and sensor configuration. This process of incorporating physical information into the 3D algorithm makes the sensor network deployment coverage improve across the physical space.

Table 4.1: Results of 3D Voronoi, GA, and CMA-ES algorithms including average coverage (AVG-coverage) and its standard deviation (SD-coverage).

Method	AVG-Coverage (%)	SD-Coverage (%)	Time(s)
3D Voronoi	98.86	0.76	646.45
GA	98.1	1.64	3898.86
CMA-ES	98.45	1.82	3264.92

4.7.4. Sensitivity and efficiency analysis

To further evaluate the efficiency of the proposed 3D Voronoi method with respect to the sensing range and the number of cameras, we tried out several experiments and present the results in Tables 4.2 and 4.3. First, the comparison of algorithm sensitivity with respect to sensing range was carried out for each method with sensing ranges 30, 50, 70, and 90 m for deploying four cameras on the fourth floor of the Convention Center. Second, the selected number of cameras was also varied, respectively, to 4, 6, 8, and 10 for each experiment to assess the efficiency of the algorithms as a function of the number of cameras. The average best coverage values, standard deviations, and computation time were determined by the algorithms for each experiment. It should be mentioned that we fixed the sensing range for assessing the number of sensors and vice versa.

Table 4.2 shows the results for the three algorithms for deploying four cameras with different sensing ranges. The performance time for all of the experiments indicated that the lowest computation cost belonged to the 3D Voronoi-based algorithm compared to the GA and CMA-ES algorithms. Concerning the sensing range, the robustness was augmented by increasing the sensing range in each experiment. For higher sensing ranges, the algorithms performed better to reach optimum, except for GA where the coverage was slightly decreased for a sensing range of 90 m.

Table 4.2: Results of 3D Voronoi, GA, and CMA-ES algorithms for four cameras.

Method	Sensing range	AVG-Coverage (%)	SD-Coverage (%)	Time (s)
3D Voronoi	30	67.44	5.69	176.62
	50	96.17	1.94	304.92
	70	98.16	1.16	486.503
	90	98.61	0.88	654.734
GA	30	70.42	6.74	2112.72
	50	93.50	2.76	2663.72
	70	98.19	2.32	3647.88
	90	97.55	1.56	3820.56

CMA-ES	30	70.74	5.98	2089.38
	50	94.68	2.20	2509.52
	70	98.08	1.60	3511.1
	90	98.52	1.21	3858.34

Regarding the number of cameras, several experiments were carried out for the deployment of 4, 6, 8, and 10 cameras using the three algorithms. The results of these experiments are shown in Table 4.3.

Table 4.3: Results of 3D Voronoi, GA, and CMA-ES algorithms for different numbers of cameras with 30 m sensing range.

Method	number of cameras	AVG-Coverage (%)	SD-Coverage (%)	Time (s)
3D Voronoi	4	67.44	5.69	176.62
	6	86.48	5.07	263.02
	8	95.42	2.01	369.82
	10	98.08	1.90	494.09
GA	4	70.42	6.74	2112.72
	6	78.93	6.32	3431.64
	8	89.68	4.24	4114.16
	10	86.70	2.89	6726.16
CMA-ES	4	70.74	5.98	2089.38
	6	86.06	6.12	3252.98
	8	86.48	3.45	4434.94
	10	90.63	2.37	5867.38

Table 4.3 indicates that when the number of cameras increased, the coverage robustness (based on the standard variation in 100 runs (column 4)) of the algorithms also increased. However, the robustness of the GA and CMA-ES algorithms was lower than the proposed 3D Voronoi-based algorithm. This is because the proposed algorithm better considers the spatial structure of the environment. Increasing the number of cameras increased the coverage value in all the algorithms. Although the coverage value was improved for the 3D Voronoi and CMA-ES, there was an exception for the GA in that it had higher coverage with 8 cameras than with 10 cameras. We presume that this occurs because of the number of parameter settings and the population size of GA, which are higher compared to those for the other algorithms. The results show that our algorithm leads to better coverage values when the number of cameras was more than six cameras compared to the GA and CMA-

ES. Finally, the results shown in Table 4.3 reveal that the computational costs of the algorithms were higher as the number of cameras increased.

4.8. Conclusions and future work

Optimal deployment of a sensor network within a 3D indoor environment is a challenging task. Traditionally, sensor placement in such environments is done using a trial-and-error method. More recently, a few optimization algorithms have been proposed for the deployment of sensor networks in indoor environments. However, these algorithms generally oversimplify the environment complexities and are mostly developed for 2D environments. In addition, they rarely consider the presence of obstacles embedded in the environment. Furthermore, in these approaches, sensing models of individual sensors are also oversimplified. Our aim in this research was to propose a new algorithm for the optimization of a sensor network in a 3D indoor environment that allows better consideration of the spatial characteristics of the environment to support applications such as mobility and security surveillance.

Here, we proposed a new local optimization algorithm based on a 3D Voronoi diagram for optimal sensor deployment in an indoor environment. The proposed optimization algorithm integrates the IndoorGML model as well as a 3D Voronoi diagram for the representation of a 3D indoor environment as well as the information of locations of the sensors and their neighborhood relations respectively. The proposed solution includes a local optimization algorithm that benefits from the 3D Voronoi data structure to define and manage sensor movement for optimization purposes. It also allows better consideration of the presence of obstacles (e.g., columns).

For the validation of the proposed algorithm, it was implemented and tested for three sensor placement scenarios (camera networks) in the Quebec Convention Center. The results show that the camera network coverage reached almost 98% from the initial random state using the 3D Voronoi approach. We also compared this method with the GA and CMA-ES algorithms to evaluate the performance of this method and showed that the final coverage value tends to an optimum value quickly and is comparable with the results obtained from the GA and CMA-ES algorithms. The algorithm tended to perform even better when the number of cameras is higher than eight for this experiment for the selected 3D indoor environment. The results also reveal that for this case study, our proposed algorithm was more than six times more efficient than the global optimization algorithms and therefore achieved optimal coverage with significantly lower computational time.

For future research, we propose to extend the capacity of the algorithm for the deployment of a multi-sensor network in an indoor environment including cameras and positioning and tracking sensors for different applications related to mobility, security, and evacuation. In addition to the environment and sensor network constraints, we will further integrate application-related constraints in the optimization of the sensor network. For instance, prioritizing sensor placement in areas where people more likely encounter problems in their wayfinding and in their mobility tasks.

Author Contributions

The design and experiments of the paper were conducted by A.A. The manuscript was written and revised by A.A. and M.A.M. All authors have read and agreed to the published version of the manuscript.

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5. Un algorithme de Voronoi 3D pour le déploiement d'un réseau de capteurs multi-types dans des environnements intérieurs complexes 3D pour faciliter la mobilité des personnes à mobilité réduite

5.1. Résumé

Les réseaux de capteurs sont de plus en plus utilisés pour la création d'environnements interactifs intelligents prenant en charge diverses applications allant de la mobilité au transport ainsi que des applications de sécurité et d'évacuation d'urgence. En particulier, l'utilisation d'un réseau de capteurs multi-types peut aider les personnes à mobilité réduite (PMR) dans leur mobilité et leur navigation au sein des environnements intérieurs complexes et leur fournir les informations nécessaires sur les obstacles et les facilitateurs et l'accessibilité de l'environnement lors de leur mobilité. Cependant, le placement optimal d'un tel réseau de capteurs reste une tâche difficile. Bien que plusieurs solutions aient été proposées pour maximiser la couverture spatiale d'un réseau de capteurs multi-types, ces solutions présentent cependant des limites lorsqu'il s'agit de déployer un réseau de capteurs multi-types dans un environnement intérieur complexe adapté pour supporter la mobilité des PMR. Ceci est dû à la complexité des environnements intérieurs 3D ainsi qu'aux besoins spécifiques pour prendre en charge la tâche de mobilité des PMR (par exemple, définition des priorités pour les zones de couverture, prise en compte des obstacles et présence de facilitateurs dans l'environnement). Cet article propose un algorithme de Voronoi 3D orienté vers l'objectif de déploiement optimal d'un réseau de capteurs multi-types dans un environnement intérieur complexe 3D en faveur de la mobilité des personnes à mobilité réduite. À cette fin, nous proposons un algorithme intégré utilisant la structure d'IndoorGML et Voronoi 3D pour la gestion des informations de l'environnement intérieur et du réseau de capteurs multi-types respectivement. Nous intégrons également des informations spécifiques sur la complexité et la lisibilité de l'environnement pour les PMR afin de guider le processus d'optimisation du réseau et de maximiser la couverture spatiale du réseau de celui-ci. Pour la validation de l'algorithme proposé, nous considérons deux types de capteurs pour la mise en œuvre : caméras (capteurs de longue portée) et capteurs Bluetooth (capteurs de courte portée). Nous comparons ensuite l'algorithme d'optimisation locale proposé vis-à-vis l'algorithme CMA-ES qui est une approche d'optimisation globale. Les résultats expérimentaux démontrent que l'algorithme proposé atteignait de meilleures performances que l'algorithme CMA-ES en matière de temps de calcule et de niveau de couverture.

Corps de l'article

Titre: A purpose-oriented 3D Voronoi algorithm for deployment of a multi-type sensor network in complex 3D indoor environments in support of the mobility of people with motor disabilities

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5.2. Abstract

Sensor networks are increasingly used for the creation of smart interactive environments in support of diverse applications ranging from mobility to transportation as well as security and emergency evacuation. In particular, the use of a multi-type sensor network can help people with motor disabilities (PWMD) in their mobility and navigation within complex indoor environments and provide them with necessary information about the accessibility of the environment during their mobility. However, optimal placement of such a sensor network is still a very challenging task. Although several solutions have been proposed to maximize the spatial coverage of multi-type sensor networks, these solutions have limitations when it comes to deploying a multi-type sensor network in a complex indoor environment adapted to support the mobility of PWMD. This is because of the complexity of 3D indoor environments as well as the specific needs to support the mobility tasks of PWMD (e.g. priority definition for the coverage areas, consideration of obstacles and facilitators present in the environment). This paper proposes a purpose-oriented 3D Voronoi algorithm for the optimal deployment of a multi-type sensor network in a 3D complex indoor environment in support of the mobility of PWMD. For this purpose, we propose an integrated an algorithm using indoorGML and a 3D Voronoi spatial data structure for the management of the information from the indoor environment as well as multi-type sensor network respectively. We also integrate specific information about the complexity and legibility of the environment for PWMD to guide sensor network optimization and maximize the new purpose-oriented weighted coverage assessment of the sensor network. To test and validate the proposed algorithm, we consider two types of sensors for the implementation: cameras (long-range sensors) and Bluetooth sensors (short-range sensors). We then compare the proposed local optimization algorithm with the covariance matrix adaptation evolution strategy (CMA-ES) which is a global optimization approach. Experimental results demonstrate that the proposed algorithm achieves a better performance than the CMA-ES algorithm in terms of computing time and coverage.

Keywords: sensor networks deployment, mobility, people with motor disabilities, legibility, multi-type sensor networks

5.3. Introduction

Over the past decades, tremendous advances have been made in wireless sensor technology with higher precision, lower cost, and smaller size to observe, monitor and track different dynamic phenomena in the environment (Argany et al., 2011). Applications of wireless sensor networks range from security purposes to traffic control as well as the monitoring of daily activities, industrial applications, and health care monitoring (e.g. virus contagion), etc. (Bertinato et al., 2008). In particular, sensors such as cameras (Reddy & Conci, 2012), Bluetooth (Chawathe, 2008), RFID (Ortakci et al., 2014), and Wi-Fi (Vera et al., 2011) are designed to measure information including: 1) the location of mobile objects, 2) the number of mobile objects, 3) their neighborhood configuration, and 4) their movement patterns in the indoor environment where GPS signals are not received due to signal loss through the walls.

One of the main challenges in the design of the sensor networks is the optimal location of the sensors in indoor environments. Optimal deployment means that dynamic data can be efficiently captured with a maximum coverage of the whole area as well as the minimization of connections between network nodes (Huang et al., 2014). Maximum coverage for sensor networks deployment has been the focus of many recent efforts. These research initiatives have resulted in variety of both global and local optimization algorithms (Argany et al., 2018). However, the multiplicity of sensor types and environmental complexity can complicate the optimization process and the results may get stuck in local optimums.

Various optimization algorithms have been proposed for the optimal deployment of sensor networks while considering the nature of the environment where the sensors are deployed. However, the environment is usually over simplified in these algorithms. In addition, these algorithms have not been designed for a specific purpose such as guiding PWMD during their mobility and navigation. For the most part, the sensors have been selected for their role in security assessment (Konda et al., 2016). However, the security goals do not prioritize the covered area based on the mobility application, and thus sensor network deployment for the latter purpose has often been accomplished manually through a trial and error process.

Most of recent research concentrates on single-type sensor network deployment; however, the deployment of multi-type sensor networks (i.e. models with different sensing ranges) offers more efficient ways to manage the network costs. Some researchers have investigated multi-type sensor network deployments with the aide of global algorithms (based on stochastic approaches) (Cao et al., 2018; Sušanj et al., 2020). The use of local algorithms, potentially cheaper, requires further investigation.

The main question of this research is to determine a method for determining the best deployment of sensor networks, in order to meet the needs of PWMD in their mobility, and which takes into account cognitive difficulties in how the environment is perceived.

Mobility is an important life habit that people accomplish when participating in their social activities (Fougeyrollas et al., 1998). However, PWMD are limited in their mobility and social participation due to the presence of numerous obstacles in the environment where they carry out their daily activities. The Disability Creation Process (DCP) model (Fougeyrollas et al., 2019) defines the level of social participation of people with disabilities as the degree of accomplishment of their life habits. The degree of accomplishment of a life habit such as mobility, depends on the result of interactions between environmental and personal factors. In such interactions, assistive technologies may play an important role to help people in their mobility. Such assistive technologies can be used to strengthen the interactions between PWMD and the environment with the aim of creating a smart and interactive built environment. A pragmatic solution to providing such a smart environment is the use of the sensor technologies to track PWMD, monitor the dynamics of the environment and send this information where it is most needed.

Furthermore, the ease with which a person recognizes his/her environment for the mobility task is denoted by the "legibility of the environment", highly related to his/her mobility performance (Weisman, 1981). The legibility of the environment is an indicator that determines where people have the most difficulties to differentiate their surrounding environment for their mobility tasks, particularly in relation to their mental representation, their cognitive map. Legibility assessment has been extensively studied in recent years, putting emphasis but without considering the impact of personal factors (Li & Klippel, 2016; O'Neill, 1991; Soltani & Ghasr, 2016; Wang et al., 2019). To personalize the issue of legibility for PWMD, a conceptual framework has been proposed in Afghantoloee et al. (2020), which provides a novel approach for the assessment of legibility of the environment for PWMD in indoor environments.

This paper proposes a purpose-oriented 3D Voronoi algorithm for the optimal deployment of a multi-type sensor network in a 3D complex indoor environment in support of the mobility of PWMD. For this purpose, we propose an integrated algorithm using indoorGML and a 3D Voronoi spatial data structure for managing the information from indoor environments as well as multi-type sensor network respectively. We also integrate specific information about the complexity and legibility of the environment for PWMD, so as guide the sensor network optimization process, and maximize the coverage of the sensor network. This research addresses the challenge of determining multi-type sensor network deployment via a local approach that incorporates information about the specific characteristics of the sensors (probabilistic sensing models for different sensing ranges, including cameras (long-range) and Bluetooth sensors (short-range)). In order to evaluate the performance of the proposed algorithm, we compare it with the CMA-ES algorithm (Akbarzadeh et al., 2011), as an example of an efficient global optimization algorithm determined by multiple case studies for deploying the different sensors. We test our algorithms for the case of the Quebec Convention Center.

The remainder of this paper is organized as follows. In Section 5.4, the relevant literatures about sensor network deployment issues for mobility are reviewed. Then, in Section 5.5, we present our novel framework and algorithm for multi-type sensor network deployment seeking to support the mobility of PWMD. The case study and the experimental results are discussed in Sections 5.6 and 5.7, respectively. Finally, conclusions and future research are presented in Section 5.8.

5.4. Literature review

The optimal deployment of sensor networks in an indoor environment is a challenging task. Researchers have sought to maximize the coverage of the network, minimize its cost (i.e. the number of sensors) and also minimize battery consumption for each sensor node, as well as to maintain a minimum connectivity between nodes (Akbarzadeh et al., 2011). Although the coverage problem has been studied intensively in several decades, there is still much to be explored. This research is mainly concentrated on the coverage problem.

Sensor network coverage estimation methods are classified into: (1) target-based coverage as a measure for detecting target points such as buildings, doors, flags and boxes, and (2) area-based coverage for the whole area detection (Guvensan & Yavuz, 2011). Methods which seek to cover target points, instead of the whole area, are focused towards a maximum number of targets. In target-based coverage, targets need to be covered by the least number of sensors (Kumar et al., 2004). The main problem in the determination of target-based coverage is the presence of obstacles, which are not generally addressed in most recent studies (Li et al., 2003; Shimosaka et al., 2016). There are a few exceptions (Roy et al., 2007), used a visibility graph as a standard structure (Welzl, 1985) has been used for evaluating inter-visibility between the sensors and intended targets.

In the area-based coverage estimation, the objective is to obtain the maximum region covered by sensors and is usually expressed as the ratio of the covered area to the whole area (Huang & Tseng, 2005). This value is directly influenced by the sensing models used. Sensing models are defined based on the characteristics of the sensors and depend on the distance and angle range limitations for their measurements. The sensing models are generally categorized into binary or probabilistic models, and omni-directional or directional sensing models (Afghantoloee et al., 2016; Akbarzadeh et al., 2013; Argany et al., 2018).

Coverage estimation is usually done based on a model of sensor's spatial representation. There are two categories for area-based spatial representations: (1) the methods that consider a raster model (Akbarzadeh et al., 2013; Argany et al., 2012; Cortes et al., 2004); and (2) the methods that model the environment as a vector dataset (Ghosh & Das, 2006; Guvensan & Yavuz, 2011; Ma et al., 2009; Wang et al., 2006; Wang & Cao, 2011). Area-based coverage estimation methods that use raster representations of the environment have disadvantages in terms of precision and efficiency. This happens because the raster representations are constrained by their spatial resolutions, and their regular shapes result in redundant data for unoccupied areas (i.e. the unoccupied pixels are incorporated into the storage volume of the raster data). Moreover, raster-based models cannot represent indoor elements such as solid objects, or columns inside a building. In contrast, vector representations overcome some of these limitations. However, most existing methods oversimplify the environmental representation and ignore the presence of diverse manmade obstacles that limit the estimation of precise coverage. More recently, Afghantoloee et al. (2014) proposed a sensor coverage estimation method based on the use of a precise 3D vector-based representation of the environment (CityGML), which can be extended to estimate sensor network coverage in an indoor environment.

Regarding sensor network optimization methods, both global and local algorithms (as well as deterministic or stochastic algorithms) have been proposed based on the maximum coverage criteria (Argany et al., 2011). Global algorithms include the Genetic Algorithm (GA) (Romoozi & Ebrahimpour-Komleh, 2012), the Particle Swarm Optimization (PSO) (Kulkarni & Venayagamoorthy, 2011), the Simulated Annealing (SA) (Niewiadomska-Szynkiewicz & Marks, 2009), and the CMA-ES (Akbarzadeh et al., 2011). These algorithms attempt to optimize a global objective function of the whole network, whereas in local algorithms such as the Virtual force-based (Zou & Chakrabarty, 2003), the VECtor-based Algorithm, and the Voronoi Algorithm (Wang et al., 2006), reconfiguration is done by changing the sensors' positions based on their local context and their proximity to other sensors.

Heterogeneity in the types of sensors within a sensor network (multi-type sensor networks) pose other challenges in the process of sensor deployment and optimization. Heterogeneity has been evaluated according to global methods in several research efforts. In global approaches, sensor heterogeneity issue is less challenging because the process of optimization considers various types of sensor models to reach the optimal coverage (Cao et al., 2018; Sušanj et al., 2020). However, some research reported used local algorithms. For example, in Tan et al. (2019)' work, a weighted Voronoi structure was employed to place different types of sensors with various sensing ranges.

The application domain and specific purpose of sensor networks (e.g., traffic, security, and mobility application) constitute another important issue in the deployment process. Purpose-related constraints are not always aligned with issues of coverage, connectivity and lifetime. For instance, Yaagoubi et al. (2015) proposed a Voronoi-based approach to deploy video sensors a security purpose (e.g., monitoring the main doors). Argany et al. (2015) conceptualized general sensor deployment as a context-aware process that not only considers local information (e.g., obstacles), and sensor parameters (e.g., sensing range), but also preferable and constrained areas for different contexts. The drawback of this conceptualization is that the needs related to the purposes were not taken into consideration.

In this study, we aim to address both issues related to the heterogeneity of the sensor nodes as well as the constraints related to the purpose of the sensor placement in an indoor environment, that is, the need to support indoor mobility and navigation of PWMD as well as, potentially, the general population. A combination of sensor types such as RFID (Ding et al., 2007; Goncalves et al., 2013; Liu et al., 2015.; Ortakci et al., 2014), Bluetooth (Delfa & Catania, 2014; Dickinson et al., 2016; Faragher & Harle, 2014; Kim, 2013), WiFi (Vera et al. 2011), and cameras (Mautz & Tilch, 2011; Reddy & Conci, 2012) can be employed to track people in an indoor environment and help them in their mobility and navigation in addition to providing them with relevant information on the accessibility and security of their routes as well as information on their points of interest.

5.5. Methodology

5.5.1. A Conceptual framework for multi-type sensor network deployment in the indoor environment with the aim of assisting the PWMD in their mobility

In this section, a conceptual model is proposed for deploying multi-type sensors in indoor environments with the aim of helping PWMD during their mobility task. There have been several efforts in recent years to develop mobility aids which use a camera network (Afghantoloee & Mostafavi, 2018). Some studies have also examined positioning accuracy using sensor networks to pin locations down (Domingo-Perez et al., 2016; Shimosaka et al., 2016; Vlasenko et al., 2015). More recently, Afghantoloee and Mostafavi (2021) developed a local optimization method for the placement of a sensor network in an indoor environment based on the 3D Voronoi diagram and indoorGML. Given the advantages of this method in terms of efficiency and the consideration of local contextual information in the optimization method, we propose to extend the method to address both the heterogeneity of the sensors as well as constraints related to mobility in support of the navigation of PWMD in indoor environments. The proposed method for sensor deployment will address not only the configuration of sensors, and contextual information but also the way PWMD interact with their environment during navigation.

To support data representation and management for different components of our proposed purposed-oriented optimization algorithm, we propose to use a) the IndoorGML structure (IndoorGML layer) for the representation of the indoor environments, b) information on sensor nodes and connections using the 3D Voronoi diagram (3D Voronoi diagram layer), and c) a legibility information layer for the management of information on the interaction of PWMD with their environment during their mobility task (Figure 5.1).

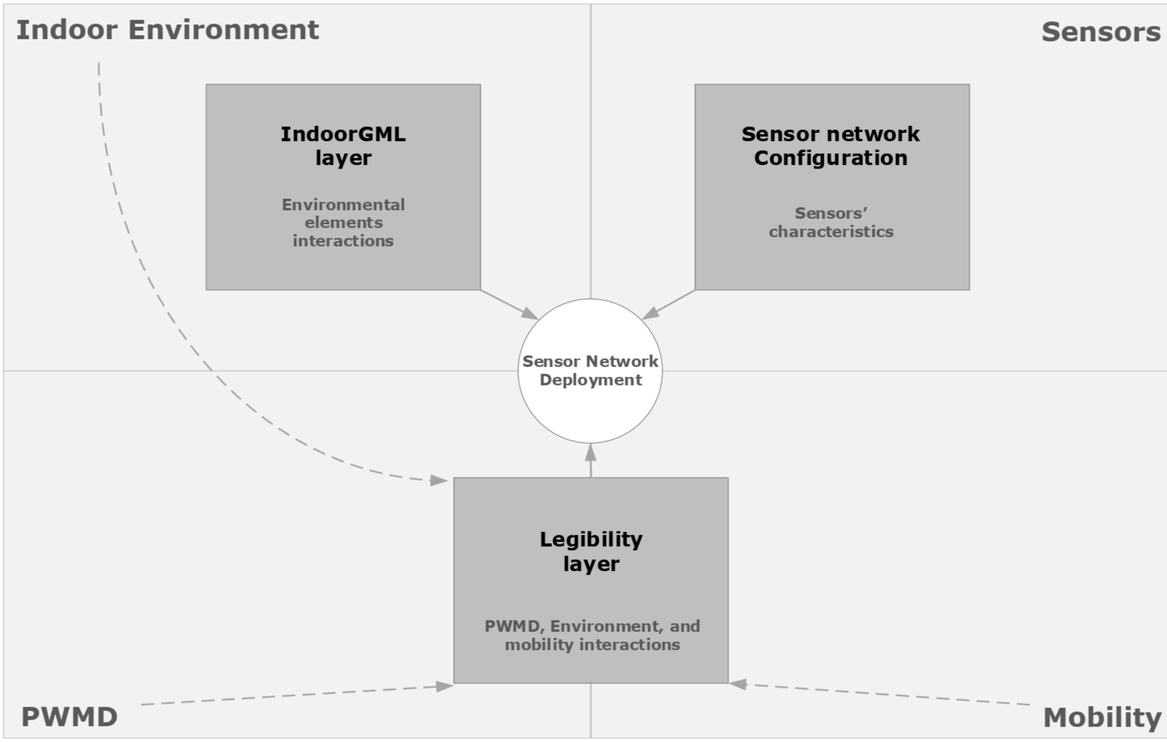


Figure 5.1: A new conceptual framework for purpose-oriented deployment based on the IndoorGML layer, sensor network configuration, and legibility layer.

To begin with, we use IndoorGML for the management of information from the environment. The structure of IndoorGML has three main modules including core modules, appearance modules, and thematic modules (Li et al., 2019). The main structure of IndoorGML divides indoor spaces into multi-spaces called cells, and the intersected area of two neighboring cells is called boundary surface (Li et al., 2019). IndoorGML uses two related spaces to model indoor environments: (1) primal space is the geometrical representation of cell space and cell boundary space, (2) dual space is the Node Relationship Graph (NRG) representing the relations between cells and their boundary surfaces, which correspond to nodes and edges respectively. There is an external reference in indoorGML that enables engines and data interpreters to link with CityGML in order to access the semantic information of surfaces such as floors, walls, and ceilings. Hence, the environment structure is classified via a set of cells stored with a central point as the node and with curves to define the cells' connections. In addition, each cell is stored based on the geometry of its surfaces. This information provides an effective approach to manage information on the indoor environment for the coverage estimation and the sensor movement strategy for optimization purposes.

With regard to the space occupied by the sensors, the 3D Voronoi diagram, as a geometrical data structure, provides an interesting model to represent sensors and their interactions within the 3D indoor environment. Each sensor is located within a Voronoi cell and only interacts with the sensors in its neighboring cells. This structure allows us not only to manage the sensor neighborhoods during the optimization process but also helps to define an effective movement strategy for sensors according to information about the neighborhood. This ensures better dispersion of sensors in the environment and also allows us to fill holes in the coverage (Argany et al., 2011). In our approach, we adapted Wang et al. (2006)'s suggestion to move sensors toward the farthest vertex of each cell in 3D space, a strategy for maximizing network coverage.

For the mobility purpose, a legibility layer is used to determine the places where PWMD encounters more difficulties during their mobility. The general legibility introduces a cognitive map as an intermediary between the designed physical environment and wayfinding performance. Personalized legibility is defined based on the interactions between PWMD and their environment where they move. Afghantoloee et al. (2020) proposed a set of factors for personalized legibility evaluation and the aggregation approach for the assessment of personalized legibility. These elements include the level of visual access, the level of connectivity, the level of complexity of the building layouts, as well as the level of accessibility of the environment considering the presence of facilitators and obstacles. This layer can be used to prioritize sensor placement where coverage is more important for guiding PWMD in an indoor environment. This prioritization affects the coverage estimation and allows us to define a new movement strategy for sensors to improve the network coverage.

Within this purpose-oriented sensor deployment method, IndoorGML, 3D Voronoi, and legibility layers are integrated to define a new coverage estimation and a strategy for moving sensors (Figure 5.2). Indeed, the coverage estimation is updated not only using environmental factors and sensor characteristics, but also via the use of a weight for the legibility layer. Hence, sensor movement, during the optimization process, is determined based on the information provided by these three components. Movement consists of displacing the sensor toward the farthest vertex of the Voronoi cell corresponding to the location of each sensor. This movement is then modified based on the lowest legibility value of the corresponding cell as well as the information on the presence of environmental factors (obstacles and facilitators), and the information on the deployable areas (walls and ceilings) provided by the indoorGML model. Note that, the movement strategy is determined not only toward the farthest vertex but also toward the spots in the legibility layer with lowest legibility.

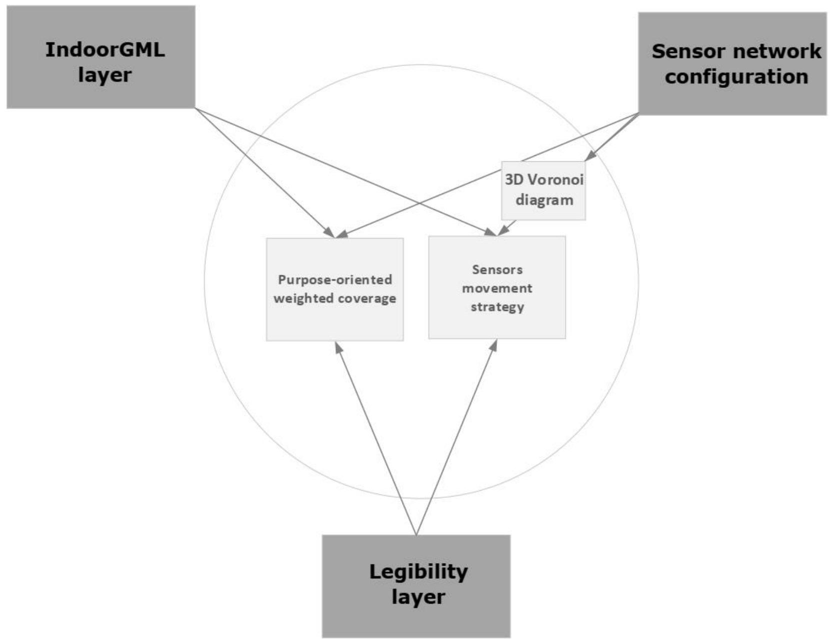


Figure 5.2: A purpose-oriented deployment process is proposed including purpose-oriented weighted coverage estimation, and sensor movement strategy.

The purpose-oriented local optimization algorithm includes the following steps:

1. ***Purpose-oriented weighted coverage (PWC) estimation based on the IndoorGML, sensor model, and legibility layer:*** As discussed previously, the coverage estimation is determined based on the sensor's position, sensing model (probabilistic omni-directional in this case), and the environmental model. Here, we assume that the target area for coverage is limited to the floor surfaces, and the sensors can be only deployed on the walls and ceilings. According to Afghantoloee et al. (2014), the covered area is estimated based on the following conditions:

    1. *If a surface (or its part) is located in the sensing range of a sensor (based on the sensor's location and model), then the surface is covered.*
    2. *If a surface (or its part) is not hidden by other objects (e.g. walls, columns) then the surface is covered by the sensor. This is verified using the line of sight to the sensor.*

    To estimate the probabilistic coverage of sensors based on their sensing range capability, visible surfaces need to be converted to a grid that allows us to determine the coverage probability value for each grid point from the deployed sensors (Afghantoloee et al., 2016).

    In this process, every point has a probabilistic coverage value which varies as a function of the sensing range (*R(i)*) and the visibility analysis between each sensor and the point *i* (*Visibility(i)*) (Figure 5.3). In addition, the inverse normalized legibility value (*Legibility(i)*) of each point is considered to be a weight which determines in turn the coverage (*PWC(i)*) for the mobility application based on the following equation.

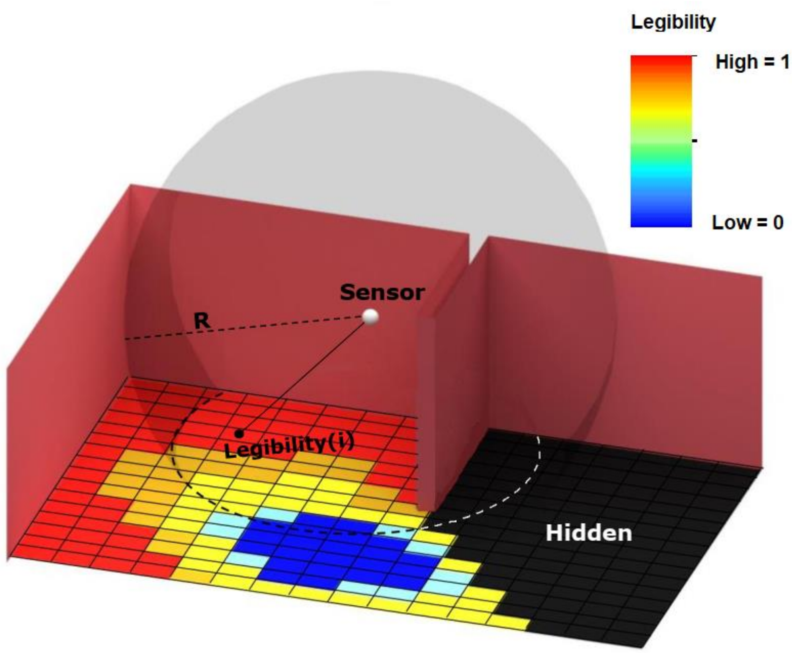


Figure 5.3: A PWC value for a sensor is estimated by its type, sensing range, environmental barriers, and legibility.

$$PWC(i) = Visibility(i) * Inversed\_Normalized(Legibility(i)) \tag{5.1}$$

$$PWC = \frac{\sum_i^n PWC(i)}{\sum_i^n Inversed\_Normalized(Legibility(i))} \tag{5.2}$$

where *n* is the number of grid points on the floor surfaces of the area which needs to be covered. *PWC* is the ratio of the sum of each *PWC(i)* to the sum of the inverse normalized legibility for each grid point *i* on the floor surface.

2. ***Movement strategy based on the 3D Voronoi diagram, legibility layer, and sensor types:*** Within the optimization process, the movement strategy for a sensor is the result of two vectors: 1) the vector ($\overrightarrow{V_{s(\iota)v}}$) indicates the orientation from a given sensor to the farthest vertex of the Voronoi cell generated by the sensor, and 2) the vector ($\overrightarrow{V_{s(\iota)L}}$) is defined from the sensor toward the lowest legible spot within the sensor's Voronoi cell (Figure 5.4). The amount of movement is equal to a step size defined based on the ratio of the sensor's sensing range ($R_{s(i)}$) to the maximum sensing range (R_{max}) in the sensor network and the length of $\overrightarrow{V_{s(\iota)v}}$ and ($\overrightarrow{V_{s(\iota)L}}$) .The lowest legible spots are determined based on the centroid of the lowest legible regions in the whole environment and prioritized based on the larger area.

The *step_size_ratio* is a variable used to control the length of the sensor's movements at each iteration to increase the exploitation rather than exploration behavior in the optimization process.

$$\overrightarrow{Movement\_S(i)} = (\overrightarrow{V_{s(i)L}} + \overrightarrow{V_{s(i)v}} * \frac{R_{s(i)}}{R_{max}}) * step\_size\_ratio \tag{5.3}$$

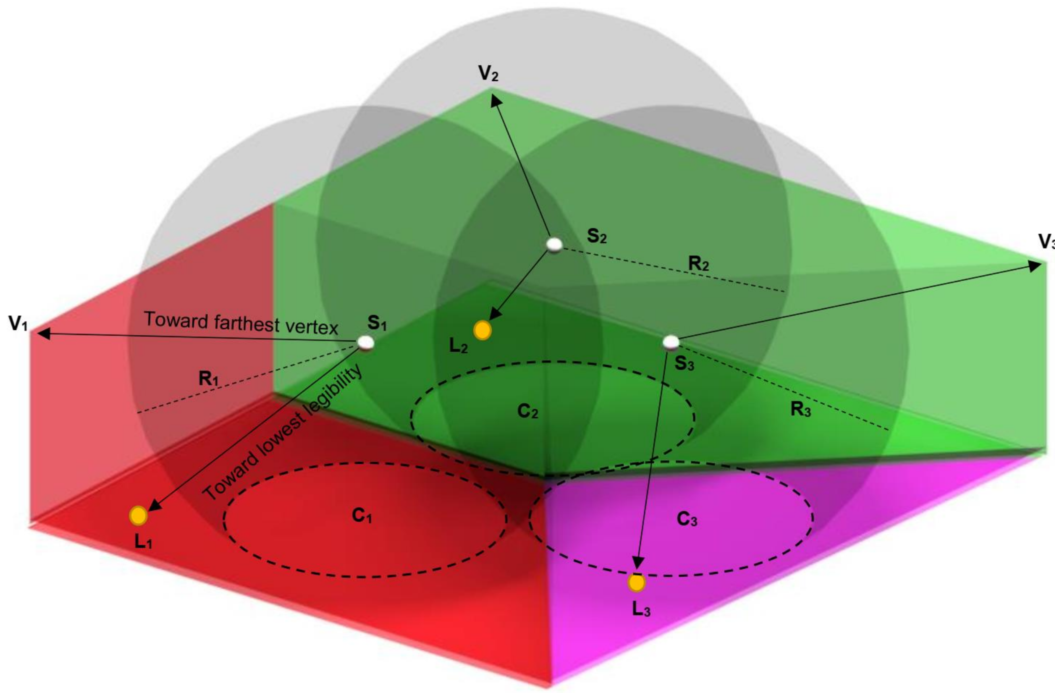


Figure 5.4: Movement strategy of sensors within their Voronoi cells is the result of the vector sum of the vector pointing toward the farthest vertex (S_1V_1), and the vector pointing toward the lowest legible spot (S_1L_1) with the step size controlled by the sensing range (R_1).

3. ***Movement strategy based on the purpose-oriented weighted coverage gain prioritization:*** Based on this strategy, at each iteration, a sensor can only move when its new position has the highest PWC gain in the network. Indeed, the PWC gain is calculated after each sensor movement and is recorded in a priority queue based on Equation 5.4. This queue is then sorted as a function of the maximum PWC gain. Finally, only the sensor with the maximum gain is moved at each iteration.

$$G_i = PWC(s_1, \dots, s_i', \dots, s_N) - PWC(s_1, \dots, s_i, \dots, s_N) \tag{5.4}$$

where G_i is the potential gain of PWC for the sensor *i*. *N* is the total number of sensors within the network.

5.5.2. A purpose-oriented 3D Voronoi algorithm based on the proposed conceptual framework

For initiating our algorithm, we make a few assumptions. We assume that sensor deployment in an indoor environment is aimed at covering areas where the legibility of the environment is poor for PWMD. It is also postulated that sensors are either a camera or a Bluetooth device, are used to position and track a person on a navigable path; furthermore, that at least one sensor is needed for the positioning purpose. Although a camera covers a wider area due to its bigger sensing radius than a Bluetooth sensor, it can be easily blocked by the presence of obstacles in the environment. Moreover, we assume that the sensors can be installed on the building's walls or ceilings and the coverage is defined on the building's floor surfaces shifted to the wheelchair's height where the PWMD's phone receives the Bluetooth signals.

Since it is assumed that the problem is defined for camera and Bluetooth sensor deployment, we define sensor models for each of these based on the sensor's characteristics such as their visibility, functionality and sensing range. Hence, we consider the camera model as an omni-directional sensor and define its coverage based on the probability of its sensing range. For this purpose, we consider the camera model with a fuzzy sigmoid membership function according to Akbarzadeh et al. (2013) as follows (Figure 5.5):

$$V_{CA}(i,j) = \left(1-\frac{1}{1+\exp(-\beta(d(i,j)-\alpha))}\right)*V_{\theta}(i,j) \tag{5.5}$$

$$V_{\theta}(i,j)=\begin{cases} 1 & \text{if there is no obstacle between camera } i \text{ and point } j \\ 0 & \text{otherwise} \end{cases} \tag{5.6}$$

where $V_{CA}(i,j)$ is the visibility probability between the camera i and the point j. $d(i,j)$ is the distance between the camera i and the point j; β and α are the configuring parameters of the camera; β shows the slope of the membership function, and α shows the distance where the visibility reaches 50% of the maximum coverage. $V_{\theta}(i,j)$ is the binary value of the visibility based on the presence of obstacles between camera i and point j.

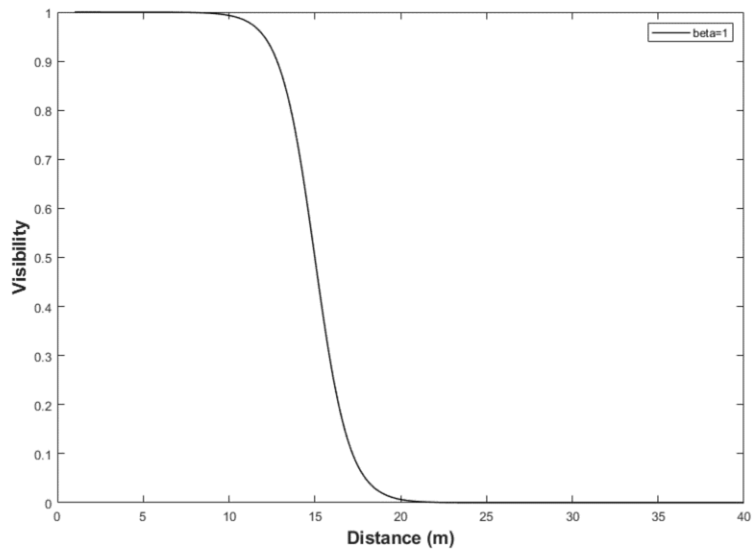


Figure 5.5: Camera visibility membership function based on its sensing range.

In the above equation, the probability of the visibility of a target for a given camera decreases with the increase in the distance between the camera and the target. α and β are the sensor configuration parameters used to define the membership function related to the physical characteristics of the camera and based on its sensing probability behavior as a function of sensing distance. It is also assumed that if the camera's line of sight intersects with obstacles such as walls, the target point is not visible to the camera.

In contrast, Bluetooth sensor visibility probability depends on the signal (dB) received from a transmitter (e.g. the personal phone). This signal decreases logarithmically by increasing the distance between the sensor and the receiver (Figure 5.6). In addition, the presence of an obstacle like a wall with a specific thickness in a specific direction (based on the angle between the direction vector of the sensor and normal vector of the wall surface) affects the amount of signal received, which reduces visibility. According to (Dao et al., 2014; Frattasi & Rosa, 2017), the visibility probability for a Bluetooth sensor is defined as follows.

$$V_{BL}(i,j) = 1 - \frac{10\log_{10} d(i,j) + k_d \sum_{l=1}^{n_w} \frac{d_l}{\cos(\varphi)}}{p_0} \tag{5.6}$$

where $d(i,j)$ is the distance between Bluetooth device i and point j; d_l denotes the thickness of the wall l; φ is the angle between the normal of the wall and Bluetooth device's line of sight; P_0 is the sensor's signal strength at 1-meter distance.

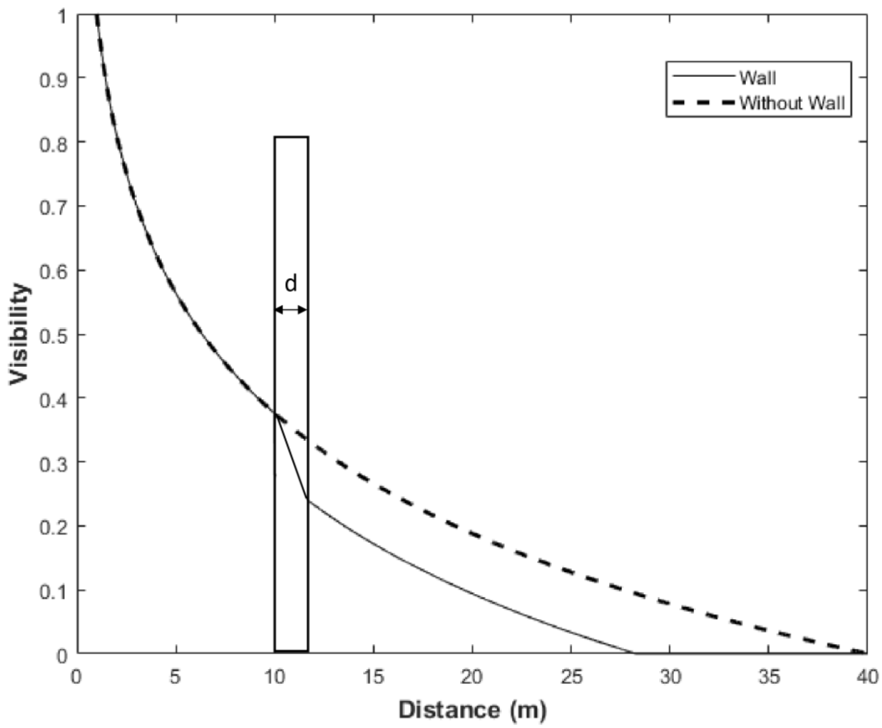


Figure 5.6: Bluetooth visibility probability path loss through a wall as a function of increasing distance (Dao et al., 2014; Frattasi & Rosa, 2017).

Here, we aim to place sensors at maximum PWC for the whole area where the PWMD-informed legibility from the environment is low. The estimation of PWC varies based on the model of the environment, the sensors sensing model and the legibility information for the PWMD. We propose an algorithm named "purpose-oriented 3D Voronoi" (PO-3DVOR) to optimize the multi-type sensors deployment with respect to these elements (Figure 5.7). With the optimal solution from this proposed algorithm, we are able to determine the location of sensors to better support PWMD in their mobility within an indoor environment.

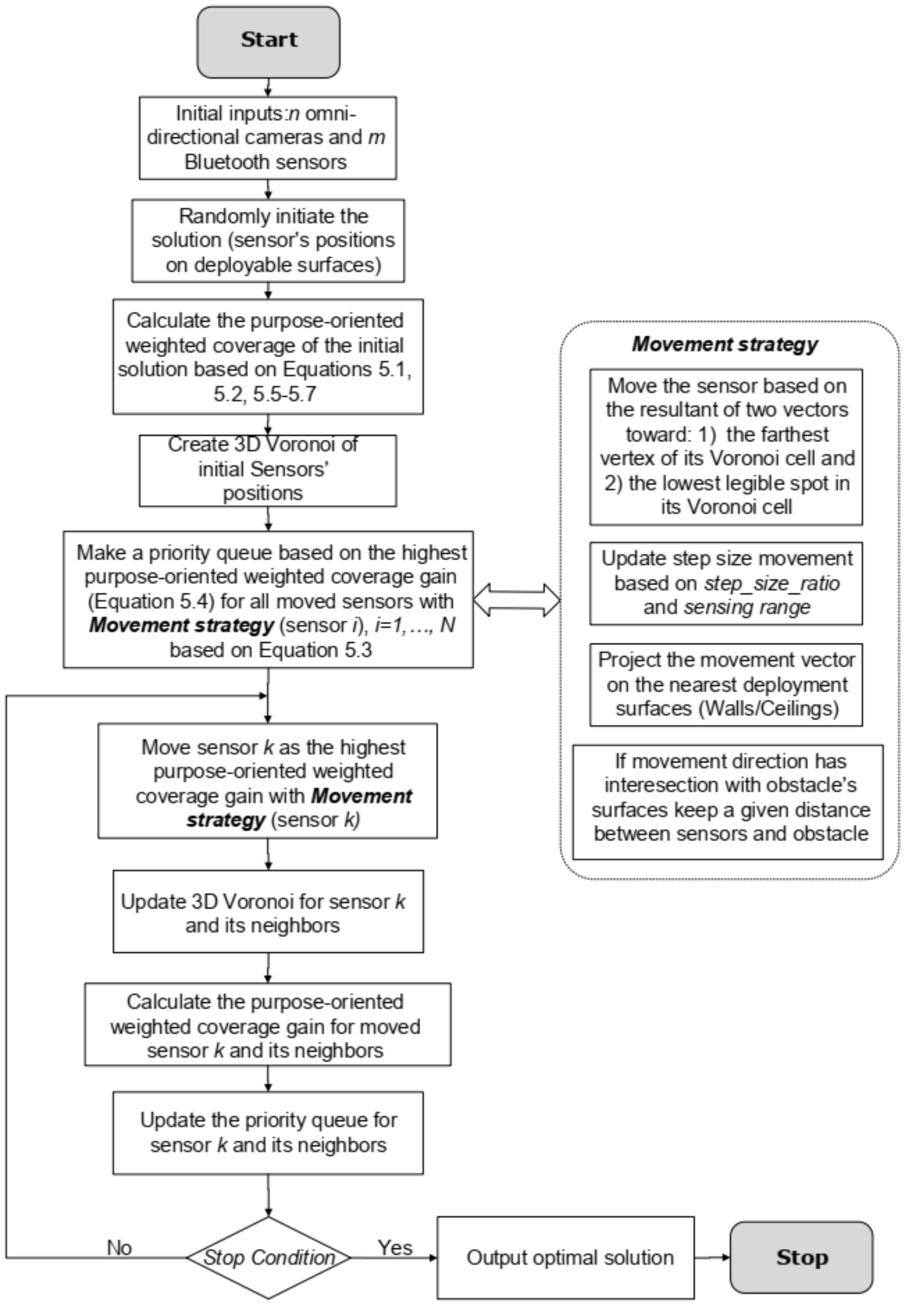


Figure 5.7: PO-3DVOR algorithm flowchart diagram

The PO-3DVOR algorithm is an iterative algorithm and is composed of several important components including the initialization with the construction of the 3D Voronoi, the PWC calculation, the application of a movement strategy for each sensor and the computation of the PWC gain as well as an update for each sensor at the end of each iteration. Initialization is the process of randomly generating solutions (sensor positions $S=\{S_1(x,y,z),\ldots,S_i(x,y,z),\ldots,S_N(x,y,z)\}$) on the deployable surfaces (walls and ceilings) in an indoor environment. In Figure 5.7, N denotes the number of sensors including the cameras and Bluetooth sensors. In addition, the environmental model (IndoorGML) and the legibility layer are prepared prior to the deployment process. The PWC of the initial solution is then calculated based on equations 5.1, 5.2, and 5.5-5.7 while taking into account the sensor's type, sensing range, the environmental model, and the legibility values. Indeed, the sensors' visibility, a principal component in the PWC, is selected based on the sensor's type with its probability range. 3D Voronoi cells are created initially based on the initial sensor positions. The movement strategy is then conducted by summing the vector toward the farthest vertex of each cell, and the vector toward the lowest legible spot within its cell. The step size of sensor movement is determined based on the sensing range and the number of iterations so that sensors with lower sensing range have lower step size than the sensors with higher sensing range, and the step size of the sensor's movement is reduced after each iteration (with *step_size_rate*). Following this, the algorithm loops through an update of the 3D Voronoi and priority queue at each iteration based on the movement strategy of a sensor with the highest gain of PWC along with those of its neighbours. The *stop condition* of this "while" loop is defined so that the maximum gain of PWC is less than a predefined gain threshold (ε) for 10 iterations in a row.

5.6. Case study

The case study that we adopt to evaluate the purpose-oriented 3D Voronoi approach is constructed for the Quebec Convention Centre, which is one of the most complex buildings in Quebec City. In this building, many events are held and large numbers of individuals participate in these events. Due to the complexity of the building and the presence of many people, the mobility of PWMD is a challenging task.

To proceed with the preparation of the necessary information layers for our algorithm, a 3D model of the fourth floor of the building was prepared and represented within indoorGML. The initial data for this model was acquired by a GeoSLAM Lidar scanner and a semi-automated method in Blender was used for the modeling process.

The sensor models for the omni-directional cameras were based on (a) Inst 360 camera model, and (b) Bluetooth low energy sensors named Estimote. The camera model was defined based on the sigmoid membership function setting with the configuring parameters (α and β), which were set to 4 and 35, respectively, for our experiments. In addition, for the Bluetooth low energy sensor model, the coefficient effect (k_d) of the wall that shows the signal strength loss was set to 2 and the maximum effective sensing range (R_{max}) for its visibility was assumed to be 40 meters. Moreover, the thickness of the walls (d_l) was assumed to be 1.4 meters. To obtain the sensor's cost, the average price of the Estimote Bluetooth sensors and the Inst 360 cameras were estimated to be 99, and 599 USD, respectively, according to market values. Based on this estimation, the price of a camera is 6 times higher than the price of a Bluetooth sensor.

Regarding the legibility layer, we used the information provided by our previous study (Afghantoloee et al., 2020). Since the sensor deployment should be done in places where the legibility of the environment is low for PWMD, the average personalized PWMD legibility is used for our purpose-weighted coverage estimation and the movement strategy of the sensors. This layer is not only applied in the estimation of PWC, but also its six regions with the lowest legibility values are extracted in order to orient the sensor movement toward the optimal PWC (Figure 5.8). The weights of these areas are prioritized with respect to the region's size.

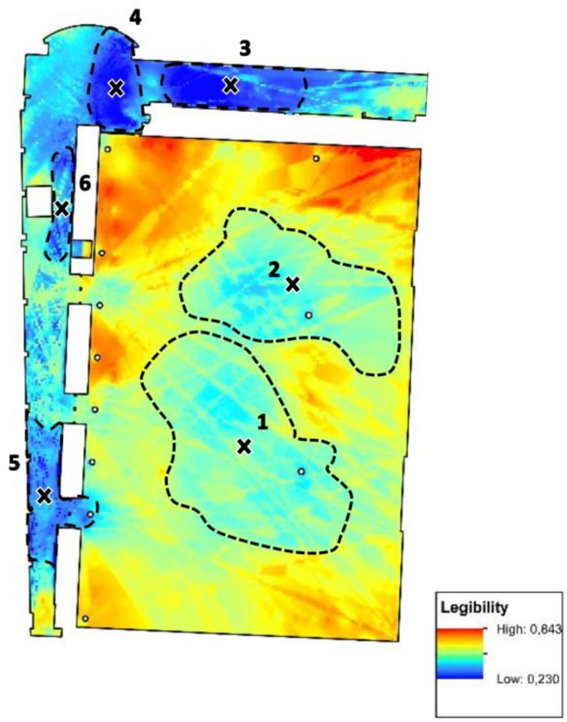


Figure 5.8: The legibility layer of the fourth floor of Quebec Convention Center with the lowest legibility regions (black dotted regions) and the lowest legibility spots (black multiplication signs) identified at the center of the regions.

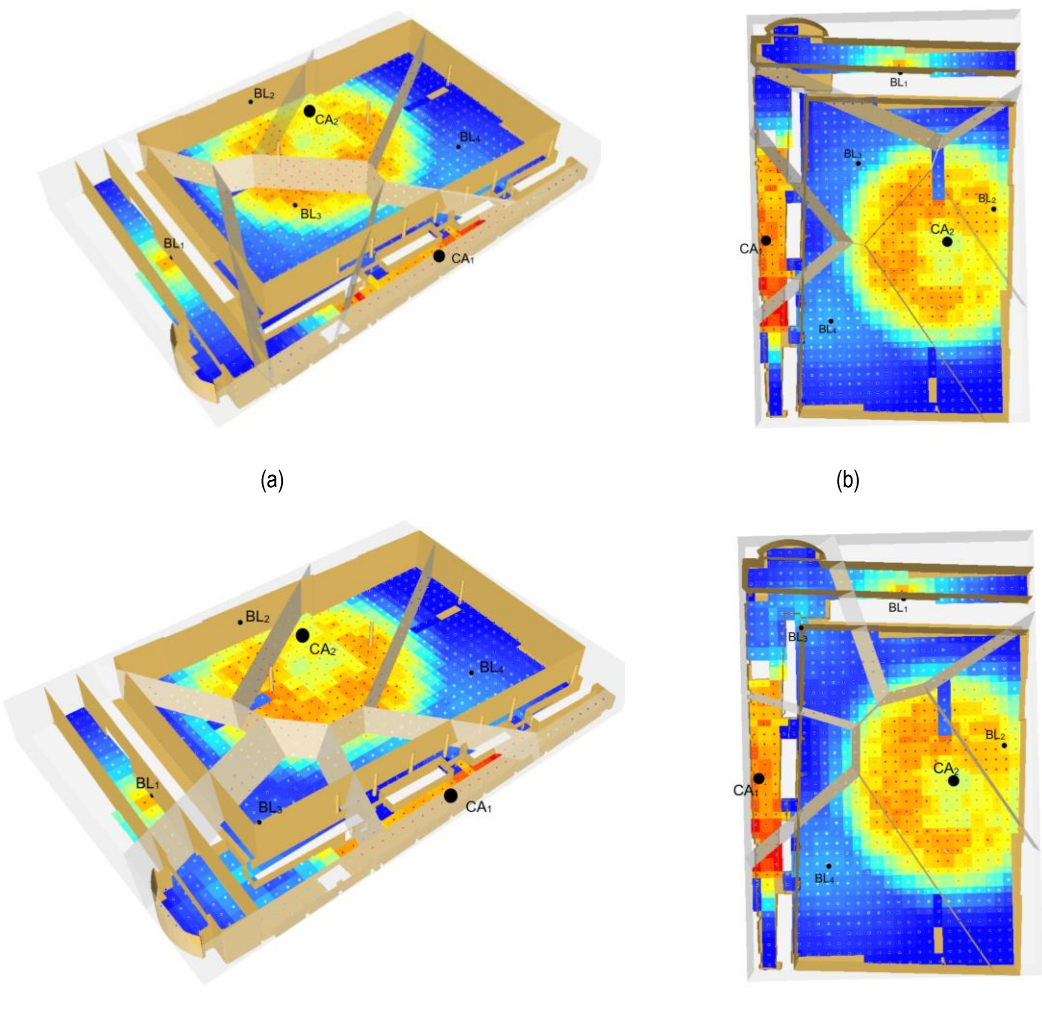
5.7. Results and discussion

In this section, we present and discuss the results from three experiments which were designed to evaluate the purpose-orientated 3D Voronoi approach (PO-3DVOR). For each experiment, the 3D indoor model of the Convention Center and its legibility layer were used. In addition, the objective of the experiments was determined in order to deploy two different types of sensors (Bluetooth low energy sensors and omni-cameras) for assisting PWMD during their mobility. Furthermore, for each experiment, the algorithm was run 100 times to prune its stochastic behavior. The average purpose-oriented weighted coverage values, their standard deviations, and the time cost of consumption were also considered to determine how good the indoor environment was covered by the sensors. To assess the reliability of our algorithm, the Covariance Matrix Adaptation Evolution Strategy

(CMA-ES) algorithm was chosen as one of the most effective global algorithms for sensor deployment optimization problems (Akbarzadeh et al., 2013).

5.7.1. Case Study I:

In the first experiment, two cameras and four Bluetooth low energy sensors were considered for the deployment problem. Figure 5.9 shows the sensor positions for the iterations 1, 2, 3, and 4 with the PO-3DVOR algorithm. The side and top view of the sensor configuration inside the building along with their corresponding Voronoi cells and the PWC of the sensor networks are depicted in the sub-figures. The output value in each grid cell illustrates the PWC value that varies from 1 to 0 (equivalent to red and blue color). Transparent surfaces indicate the boundaries of Voronoi cells for each sensor.



(a) (b)

(c) (d)

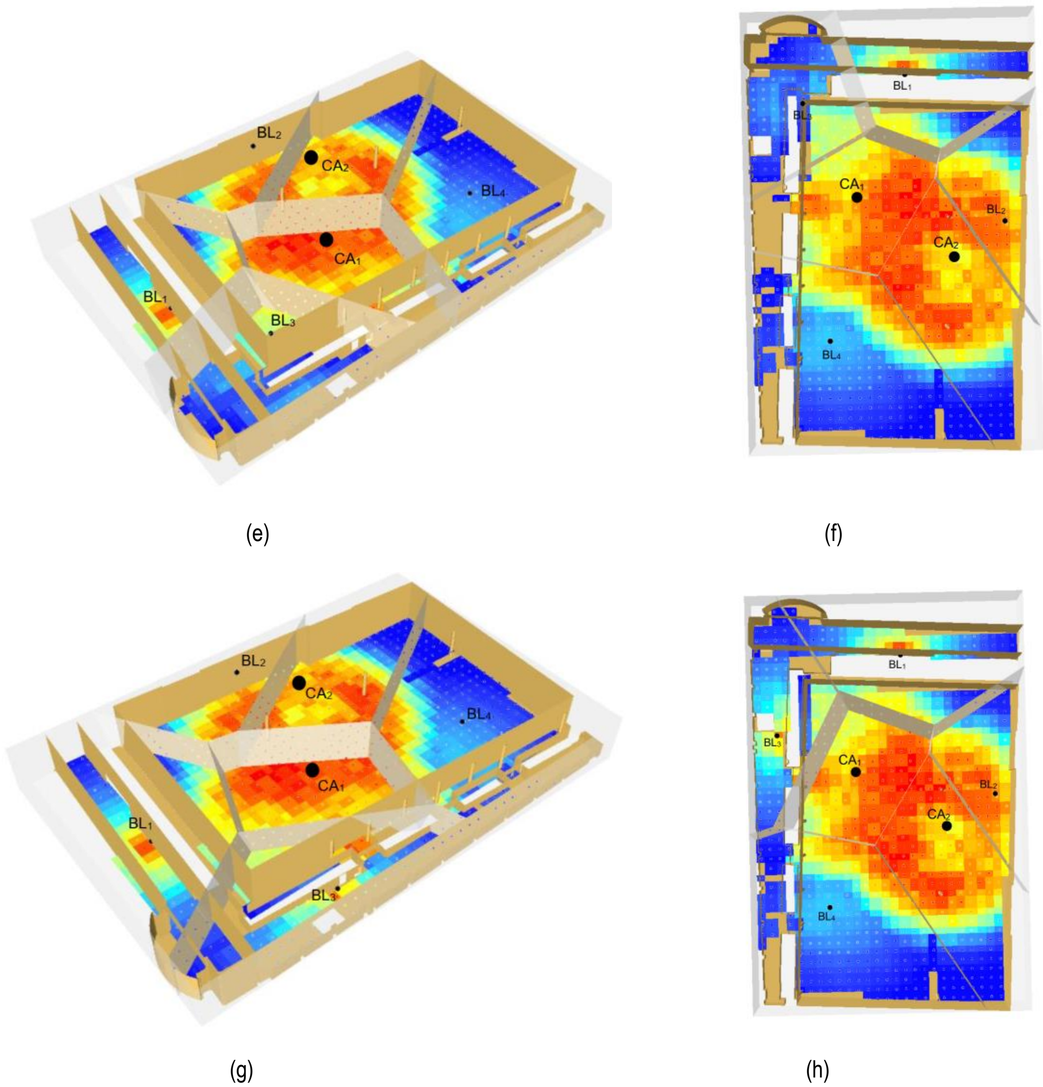
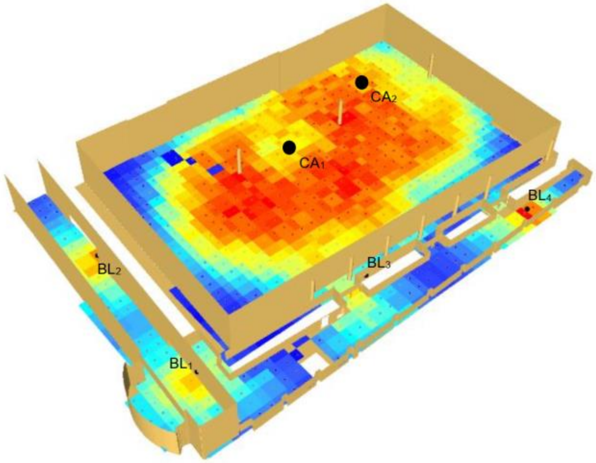
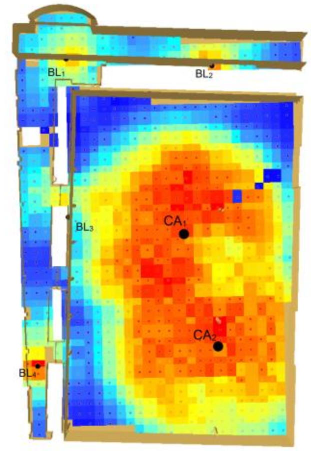


Figure 5.9: The results are shown for the first four iterations of the PO-3DVOR method in side and top perspective views.

The final result produced by the PO-3DVOR algorithm is shown in Figure 5.10. This figure shows that not only were the sensors well-distributed in the environment, but they were also located in the areas where the value of PWC was high. Additionally, as the cameras had a wider sensing range than the Bluetooth sensors, they were deployed in the largest cell with the higher coverage values. The results also show that the distances between sensors and obstacles were also concluded in the calculation in order to reduce their impact on resulting coverage.



(a)



(b)

Figure 5.10: The final optimal configuration of sensors with the PWC values by the PO-3DVOR approach, (a) side, and (b) top view.

The use of sensor movement toward the areas with the lowest legibility values besides greatly increased the speed of achieving the optimal PWC (Figure 5.11). Similarly, consideration of the sensing range of the sensors in the movement strategy also increased the process of achieving convergence in the PO-3DVOR approach to an adequate optimum.

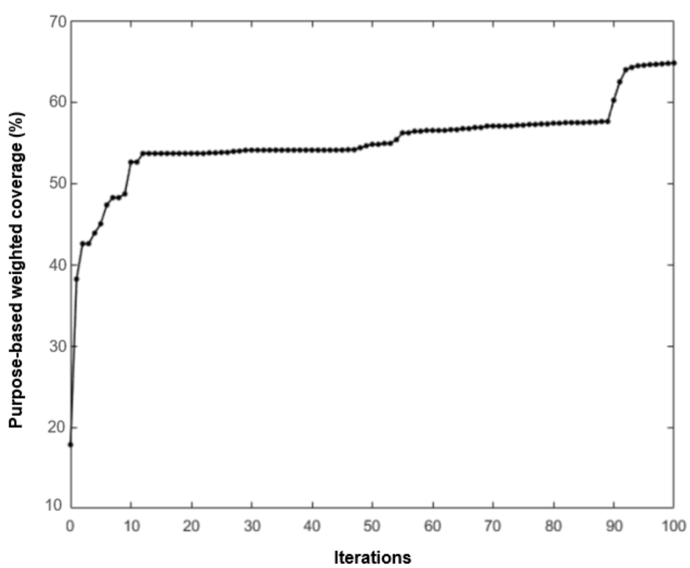


Figure 5.11: The convergence diagram of PO-3DVOR approach.

Here, we evaluate the performance of the PO-3DVOR algorithm according to the different movement strategies, and also the effect of sensor's motion step size variations for the different sensing ranges. For this purpose, first, the PO-3DVOR algorithm was performed while only considering the PWC estimations in 100 runs (condition 1). Second, the PO-3DVOR algorithm was modified by adding the sensor's movement toward the lowest legible spots inside the building (condition 2). The PO-3DVOR algorithm was finally modified with respect to the strategy of movement based on the different sensing ranges (condition 3). The final results of these algorithms with respect to the different strategies were compared in Table 5.1. Experimental results in Table 5.1 show that the proposed PO-3DVOR algorithm outperforms other conditions in terms of higher PWC (column 2) and lower standard deviation of PWC (column 3).

Table 5.1: Results of different strategies of sensor's movement

Method	AVG-PWC(%)	SD-PWC (%)	Time (s)
Conditon 1	59.34	3.56	335.67
Condition 2	63.45	2.56	365.25
Condition 3	61.70	3.58	347.23
PO-3DVOR	65.06	2.12	375.50
CMA-ES	57.37	5.24	826.12

To assess the reliability of the PO-3DVOR algorithm in general, the problem of the multi-type sensor deployment to assist PWMD in their mobility was performed using the CMA-ES as an efficient global algorithm in 100 runs. In this algorithm, the calculation of the objective function was based on the estimation of PWC presented in the paper. Hence, the sensors were randomly deployed in the 3D space (3D bounding box of the building) and they were projected to the nearest deployable surfaces (walls and ceilings). In addition, the setting parameters of CMA-ES including population (λ), the formation of solution's means and direction (σ) were considered to be 3+4*[ln(n)] (n = 3*(the number of sensors)), λ/2, and 0.167, respectively. The result of two cameras and four Bluetooth sensors deployment by the CMA-ES algorithm is shown in Table 5.1.

5.7.2. Case Study II:

In order to compare the number of sensors and the effectiveness of the PWC in the optimization process, more experiments were conducted by changing the number of sensors. In these experiments, it was assumed that the maximum cost for using sensors (cameras and Bluetooth sensors) is fixed. In this regard, the deploying cost of 20 Bluetooth sensors is equivalent to the deploying cost of two cameras according to their market value. Accordingly, experiments were firstly performed on a small number of cameras (0, 1 and 2) and a large number of Bluetooth sensors (10-12-14-16-18-20). The results show that the PO-3DVOR algorithm necessitates a lower execution time compared to CMA-ES algorithm in all categories (Table 5.2).

Table 5.2: Average and standard deviation of PWC, and computing times for determining the deployment of Bluetooth and cameras (with a dense configuration of Bluetooth sensors)

BLE	Camera	Cost (USD)	AVG -PWC (%)	SD-PWC (%)	Times (s)

Number	Number	Sensors numbers and prices	PO-3DVOR	CMA-ES	PO-3DVOR	CMA-ES	PO-3DVOR	CMA-ES
10	0	990	28.05	24.58	0.75	0.65	708.75	1440.13
	1	1589	54.16	52.32	0.88	4.27	862.62	1673.36
	2	2188	69.81	64.87	3.92	4.36	1086.34	1706.45
12	0	1188	29.94	26.60	0.85	0.53	1061.81	1682.80
	1	1787	50.89	50.36	6.01	7.96	1042.81	2435.02
	2	2386	70.78	66.95	3.40	4.17	1304.08	2113.21
14	0	1386	32.05	27.45	0.62	0.57	1276.37	2022.43
	1	1985	55.34	53.94	0.46	4.51	1338.49	2151.34
	2	2584	69.98	68.84	3.50	3.85	1575.38	2382.17
16	0	1584	33.34	28.73	0.55	0.95	1551.32	2259.02
	1	2183	56.47	51.48	5.91	4.01	1708.45	2442.87
	2	2782	69.79	67.69	3.92	4.90	1967.02	2643.74
18	0	1782	34.96	29.61	0.46	0.49	1845.94	2540.09
	1	2381	54.54	54.56	0.82	6.92	1987.93	2914.35
	2	2980	71.81	69.20	2.67	3.15	2240.92	3041.22
20	0	1980	36.42	30.45	0.65	0.63	2149.05	2974.59
	1	2579	57.85	55.72	0.50	4.72	2298.21	3225.60
	2	3178	67.82	69.22	3.03	5.38	2511.26	3328.22

5.7.3. Case Study III:

In the final experiment, the number of cameras was increased to a maximum of 4 with a smaller number of Bluetooth sensors (4-6-8-10). In this experiment, the evaluation was carried out based on the average values of purpose-weighted coverage, and the standard deviation over all 100 runs for the PO-3DVOR and CMA-ES algorithms. In addition, the execution time of each algorithm and cost of deployment were estimated based on the average of runs and sensor types. The overall results of these tests are shown in Table 5.3. As we can see, some cases exhibit empty values for the PO-3DVOR algorithm because the 3D Voronoi structure can only be constructed for at least 4 points. The results showed again, however, that the execution time of the PO-3DVOR is lower than CMA-ES in all test cases.

Table 5.3: Average and standard deviation of PWC, and computing times for deployment of Bluetooth and cameras (with low numbers of Bluetooth sensors)

Camera	BLE	Cost (USD)	AVG-PWC (%)		SD-PWC (%)		Times (s)	
Number	Number	Sensors numbers and prices	PO-3DVOR	CMA-ES	PO-3DVOR	CMA-ES	PO-3DVOR	CMA-ES
0	4	396	16.86	16.03	1.11	0.80	189.78	496.74
	6	594	21.78	20.04	0.76	0.58	326.50	758.65
	8	792	25.43	23.23	0.67	0.76	500.55	1056.07
	10	990	28.05	24.58	0.75	0.65	708.75	1440.13
1	0	599	-	35.94	-	4.40	-	
	4	995	42.41	47.47	0.79	5.99	269.00	660
	6	1193	45.58	47.82	4.57	6.30	442.64	955.81
	8	1391	48.74	47.04	7.62	7.29	628.30	1196.40
	10	1589	54.16	52.32	0.88	4.27	862.62	1673.36
2	0	1198	-	54.35	-	9.57	-	
	4	1594	61.51	63.31	4.95	4.16	376.10	799.12
	6	1792	63.29	65.27	3.76	7.65	587.34	1116.60
	8	1990	66.30	67.47	2.90	3.71	813.75	1433.36
	10	2188	69.81	64.87	3.92	4.36	1086.34	1706.45
3	0	1797	-	67.95	-	2.22	-	
	4	2193	73.81	73.57	3.41	3.73	487.61	1017.26
	6	2391	75.63	74.10	1.60	3.50	719.76	1260.53
	8	2589	75.20	74.35	1.81	3.67	995.10	1597.60
	10	2787	75.45	75.54	1.65	4.71	1214.58	1842.37
4	0	2396	74.78	76.34	2.79	3.65	189.78	496.74
	4	2792	80.30	77.50	2.00	1.31	641.87	1168.26
	6	2990	80.18	79.26	2.11	2.57	871.27	1508.65
	8	3188	81.52	79.88	1.63	3.03	1129.94	1739.91
	10	3386	82.09	81.17	1.67	2.78	1348.86	2121.75

In order to compare the results of the two algorithms based on these experiments, we credited a win score for the algorithm that had the higher score as a result of having higher coverage and lower standard deviation for the different categories, that is, including the average (AVG), minimum (MIN), maximum (MAX), and standard deviation (SD) for 100 runs for each test case. The resulting win counts are shown in Figure 5.12.

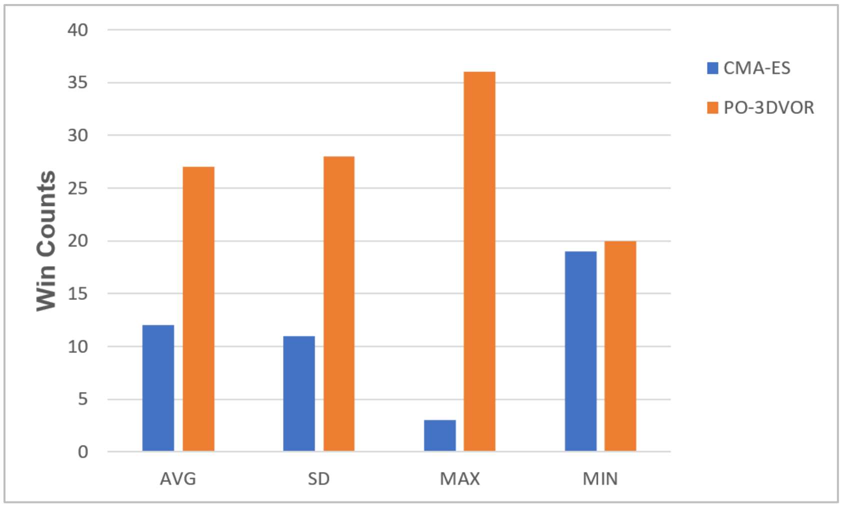


Figure 5.12: Win counts for algorithms in all the experiments.

Based on the win counts of Figure 5.12, the PO-3DVOR algorithm gave the higher counts in all categories. Both with regard to its average and standard deviation values, the PO-3DVOR algorithm obtained almost twice the win score of the CMA-ES algorithm. In addition, the maximum coverage of the PO-3DVOR algorithm was higher than that of the CMA-ES algorithm in most cases. It should also be mentioned that the CMA-ES algorithm generated an almost equal number of wins based on its minimum values.

These results suggest that the PO-3DVOR algorithm offers several advantages over the CMA-ES algorithm. First, the PO-3DVOR performance time is much better than that of the CMA-ES algorithm. Second, the PO-3DVOR algorithm generated a better result in terms of PWC as well as a smaller standard deviation most of the time. Third, the maximum PWC for 100 runs was higher for the PO-3DVOR algorithm than for the CMA-ES algorithm. And finally, the PO-3DVOR algorithm can handle a larger variety of the environments including multi-floor structures, while using the same approach for both the sensor movement and coverage estimation.

However, there are also some limitations associated with the PO-3DVOR algorithm. The main limitation was that when adding constraints such as a k-coverage estimation (the area covered by at least k sensors) in order to obtain better precision, the algorithm needed to be modified. In addition, the use of directional sensors required extending the algorithm so that the rotation strategy for the sensors could be defined according to the legibility, environmental and sensor characteristics.

5.8. Conclusions and future work

In this paper, a purpose-oriented method based on the 3D Voronoi diagram for the deployment of different types of sensors in indoor environments to assist the PWMD during their mobility is proposed. Our method incorporates information from indoor environment as represented by indoorGML, information on the legibility layer of the environment for PWMD, as well as information on sensors and on their configuration (3D Voronoi diagram).

For evaluation purpose, the proposed method was used to deploy sensors in the Quebec City Convention Center. The legibility information layer was used to optimize the sensor deployment process for PWMD based on both personal and environmental factors as determined for the Convention Center. The method was designed to maximize the coverage of the environment and prioritize the regions where legibility is low for PWMD. In the deployment process, multi-type sensors were considered in the calculation of probabilistic coverage and also the exploration of solutions for sensors with shorter sensing range have lower step size in their movement than the sensors with larger sensing range.

A comparison of the proposed method (the PO-3DVOR algorithm) through different development steps showed that the combination of the environmental model (condition 1), legibility layer (condition 2) and sensing range (condition 3) gave the best result for the maximization of PWC. In addition, the PO-3DVOR algorithm led to robust solutions with the lowest standard deviation of PWC.

To study the reliability and performance of the proposed algorithm, this was compared to the CMA-ES method as a previously tested effective global method. Our results reveal that the execution time of the PO-3DVOR algorithm is significantly lower than that of the CMA-ES algorithm, because the CMA-ES performance time requires a large number of solutions. In addition, the PO-3DVOR algorithm generates lower standard deviation of PWC than does the CMA-ES method.

In the future, we will focus on other types of sensors, especially those with directional limited ranges. Moreover, a k-coverage (i.e., the area has to be covered by at least k sensors) objective will be considered for more precise positioning and tracking using approaches such as triangulation. Another extension to this work will be to consider the integration of actuators as well as sensors in the optimal deployment process. Actuators such as dynamic signs would be useful to enhance the ability of PWMD to find the right route to their destination with the aim of helping them to be independent in their mobility.

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Conclusion

6.1. Résumé

Cette thèse porte sur le déploiement optimal de capteurs dans l'environnement intérieur où les PMR ont besoin de plus d'aide pendant leur mobilité. Elle propose un nouvel algorithme d'optimisation locale basé sur la structure Voronoi 3D et IndoorGML comme modèle de l'environnement ainsi qu'une couche de lisibilité déterminée en fonction des PMR à partir de l'environnement intérieur. Les principales contributions de cette thèse ont été de proposer un nouveau cadre d'évaluation de la lisibilité de l'environnement intérieur qui tient compte du profil des PMR, de proposer un cadre de déploiement de capteurs avec l'intégration des modèles Voronoi 3D et IndoorGML et l'intégration de ces deux cadres pour améliorer la couverture des réseaux de capteurs, en particulier, là où la lisibilité des PMR est médiocre.

Dans le chapitre 1, le contexte, les problèmes généraux et spécifiques, les objectifs de la recherche et les phases méthodologiques ont été présentés. Cette recherche propose une nouvelle solution d'optimisation des réseaux de capteurs non seulement pour améliorer la couverture du réseau, mais aussi pour mieux aider les PMR lors de leur mobilité dans un environnement intérieur complexe. Nous avons argumenté que la complexité de l'environnement intérieur et le besoin qu'il y ait une meilleure couverture du réseau pour aider les PMR compliquent le processus d'optimisation de déploiement des capteurs. En tenant compte des caractéristiques de l'environnement intérieur telles que divers obstacles, différentes hauteurs de plafonds, les relations complexes entre les éléments ainsi que la perception des PMR, nous avons identifié plusieurs problèmes spécifiques dont : 1) le problème de l'intégration des facteurs personnels et environnementaux pour définir une meilleure évaluation de la lisibilité à partir des perceptions et de la représentation mentale des PMR, 2) le problème de placement des capteurs dans l'environnement intérieur complexe avec une approche d'optimisation locale et 3) le problème concernant la complexité du déploiement en présence de capteurs multi-types.

Dans le chapitre 2, l'état de l'art sur la mobilité, les systèmes de navigation, les technologies de capteurs et les problèmes de déploiement et optimisation de réseaux de capteurs a été présenté. Premièrement, nous avons passé en revue les enjeux de mobilité des PMR en lien avec l'accessibilité et la lisibilité de l'environnement intérieur. Ensuite, plusieurs technologies d'assistance à la navigation ont été présentées. De plus, l'importance de l'environnement dynamique a été présentée ainsi que le besoin de placer des capteurs pour différentes situations telles que l'évacuation. Par la suite, les divers problèmes liés au déploiement et à l'optimisation d'un réseau de capteurs ont été élaborés, incluant l'estimation de la couverture spatiale du réseau en fonction du modèle des capteurs, l'évaluation de l'impact de l'environnement intérieur sur le déploiement de capteurs ainsi que les choix parmi les algorithmes d'optimisation. Enfin, notre revue de la littérature a révélé que la plupart des méthodes de déploiement de capteurs ne considèrent pas la complexité de l'environnement intérieur et les besoins spécifiques de mobilité des PMR.

Les chapitres 3 à 5 présentent les contributions originales de cette thèse sous forme d'articles publiés ou soumis à des revues scientifiques avec comités de lecteurs. Ils présentent les concepts et les algorithmes originaux proposés dans ce travail de recherche.

Au chapitre 3, les problèmes d'évaluation de la lisibilité des PMR pour un environnement intérieur et de sa personnalisation ont été étudiés. Afin d'évaluer la lisibilité personnalisée de l'environnement intérieur en fonction des PMR, un cadre conceptuel a été proposé se basant sur le modèle PPH (Fougeyrollas et al., 2019) et la notion de l'affordance de Gibson (1994). Le concept proposé considère les facteurs personnels et environnementaux ainsi que la capacité et l'expérience de différents profils des PMR dans l'évaluation de la lisibilité. Dans cette recherche, la lisibilité a été définie comme le résultat des interactions entre les PMR et leur environnement. Plus spécifiquement, l'accessibilité de l'environnement pour les PMR et la présence des facilitateurs et d'obstacles ont été intégrées à d'autres facteurs étudiés auparavant pour la question de la lisibilité. Pour la validation du concept proposé, la lisibilité de l'environnement intérieur du Centre des congrès de Québec du point de vue d'une personne utilisatrice de fauteuil roulant manuel a été considérée dans nos études de cas.

Au chapitre 4, le déploiement optimal d'un réseau de capteurs dans l'environnement intérieur visant de fournir une aide pour la mobilité des PMR a été étudié. Nous avons, plus spécifiquement, mis l'emphase sur la complexité de l'environnement intérieur, sur sa représentation et sur les impacts de ceux-ci sur l'estimation de la couverture spatiale du réseau. Cette recherche nous a conduit à proposer un cadre conceptuel pour le déploiement de capteurs dans l'environnement intérieur complexe 3D. La méthode se base à la fois sur le diagramme Voronoi 3D et sur la structure de données d'IndoorGML comme modèle de représentation de l'environnement intérieur. Ensuite, un nouvel algorithme d'optimisation locale a été développé sur la base du cadre conceptuel proposé en considérant la structure Voronoi 3D et IndoorGML afin de prendre en compte les interactions entre les capteurs et les éléments environnementaux dans le processus de déploiement. Finalement, l'algorithme proposé a été testé dans différents scénarios d'expérimentation en tenant compte de la présence des obstacles et de différents nombres de capteurs au Centre des congrès de Québec. Les résultats obtenus ont été comparés à ceux obtenus avec d'autres algorithmes d'optimisation, notamment l'algorithme GA et l'algorithme CMA-ES.

Dans le chapitre 5, l'objectif de mobilité a été considéré dans le processus de déploiement des capteurs. Un nouvel algorithme d'optimisation locale orienté vers l'objectif de mobilité a été développé pour le déploiement des capteurs basé sur le cadre proposé. De plus, cet algorithme a été mis en application dans le contexte de capteurs multi-types (c'est-à-dire différents modèles de capteurs, par exemple, des caméras omnidirectionnelles et des capteurs Bluetooth avec des champs de détection différents). Par la suite, des expérimentations ont été faites pour évaluer la performance de l'algorithme proposé en le comparant avec l'algorithme CMA-ES. Finalement, une évaluation de la sensibilité de l'algorithme au nombre de capteurs et leurs types (différents nombres de caméras et de capteurs Bluetooth) a été réalisée en différentes expérimentations.

6.2. Discussions et conclusions

Dans cette recherche, nous avons proposé un nouveau cadre conceptuel pour évaluer la lisibilité de l'environnement intérieur pour les PMR. Les facteurs personnels et environnementaux ont été intégrés pour l'évaluation de la lisibilité. Cette idée a été inspirée par le modèle PPH qui définit la situation du handicap comme le résultat des interactions entre une personne et son environnement. En outre, ce cadre intègre plus particulièrement les éléments saillants visuels et des accessibilités (les obstacles et les facilitateurs) des environnements intérieurs. En conclusion, la couche de lisibilité a été créée par rapport aux facteurs de lisibilité tels que le niveau de visibilité, la connectivité, la complexité et l'accessibilité pour le Centre des congrès de Québec.

Dans ce processus, et par souci de simplicité, nous avons fait plusieurs hypothèses pour produire les résultats présentés. Par exemple, nous avons calculé des valeurs de lisibilité plus génériques pour l'ensemble de la population avec et sans incapacité physique qui doivent être précisées dans de futures expérimentations pour des PMR spécifiques. De plus, nous n'avons pas défini de pondérations spécifiques pour chaque facteur en fonction de la signification. En fait, nos résultats dans l'étude de cas ont été obtenus en supposant que les poids des facteurs de lisibilité proposés étaient égaux. Cependant, l'importance des facteurs de lisibilité peut être modifiée en fonction du profil d'un individu. Ainsi, afin de déterminer précisément le poids de chaque facteur de lisibilité, il est nécessaire d'évaluer les performances de mobilité des PMR (avec différents profils) dans l'environnement. Cela doit être étudié plus en détail dans les recherches futures.

Ensuite, nous avons développé une nouvelle méthode d'optimisation locale basée sur le diagramme Voronoi 3D pour guider le déploiement de capteurs dans l'environnement intérieur complexe. Pour cela, les informations sur des capteurs et sur l'environnement ont été intégrées pour améliorer la couverture d'un réseau sans fil. Nous avons utilisé le modèle IndoorGML pour prendre en charge les interactions entre les éléments environnementaux tels que les différentes cellules (par exemple, les couloirs et les halls) et les surfaces (les planchers, les plafonds et les murs) pour estimer la couverture du réseau et déterminer la stratégie de mouvement des capteurs vers une configuration optimale (la couverture maximale). La comparaison des résultats de cette méthode avec les algorithmes GA et CMA-ES, deux algorithmes d'optimisation globale déjà connus, a été faite. Les résultats montrent que la couverture du réseau a atteint près de 98 % en utilisant l'approche Voronoi 3D et que la valeur de couverture finale est comparable à celles obtenues à partir des algorithmes GA et CMA-ES. Les résultats révèlent également que pour cette étude de cas, notre algorithme est six fois plus efficace que les algorithmes d'optimisation globale.

Cet algorithme n'a pas la capacité de déployer un réseau de capteurs multi-types dans un environnement intérieur comprenant des caméras et des capteurs de positionnement pour différentes applications liées à la mobilité, à la sécurité et à l'évacuation. En plus des contraintes d'environnement et de réseau de capteurs, les contraintes liées à l'application dans cette approche d'optimisation n'ont pas été prises en compte pour le déploiement des capteurs. Par exemple, donner la priorité au placement des capteurs dans les zones où les gens rencontrent le plus de problèmes dans leur orientation et dans leurs tâches de mobilité.

L'optimisation du réseau de capteurs multi-types pour guider des PMR était la dernière étape de développement de l'environnement interactif pour améliorer la mobilité des PMR dans des environnements très complexes. L'approche d'optimisation locale a été développée avec l'intégration des informations des capteurs, de l'environnement et de la lisibilité de l'environnement pour les PMR. Différents tests d'évaluation avec différents types de configurations de capteurs nous ont permis de valider notre méthode en le comparant à l'algorithme CMA-ES. Cependant, ces tests ont également relevé que la consommation du temps de calcul de notre approche est significativement inférieure à celui de l'algorithme CMA-ES, car le temps de performance du CMAES est basé sur l'estimation de la couverture pondérée pour un grand nombre de solutions. De plus, notre approche à un écart-type plus faible de la couverture pondérée basée sur l'objectif du CMA-ES.

Cependant, il existe également certaines limitations associées à cet algorithme. La principale limitation était que lors de l'ajout de contraintes telles qu'une estimation de k-couverture (la zone couverte par au moins k capteurs) afin d'obtenir une meilleure précision, l'algorithme devait être modifié. De plus, l'utilisation de capteurs directionnels a nécessité d'étendre l'algorithme afin de pouvoir définir la stratégie de rotation des capteurs en fonction de la lisibilité, de l'environnement et des caractéristiques des capteurs.

La contribution majeure de cette recherche est d'intégrer les informations de l'environnement intérieur, la lisibilité des PMR de l'environnement et les informations du réseau de capteurs pour un déploiement optimal du réseau dans le but d'aider les PMR dans leur navigation intérieure. Les contributions spécifiques sont réalisées en lien avec les trois objectifs spécifiques de cette recherche: 1) proposer un nouveau cadre conceptuel de la lisibilité de l'environnement intérieur pour les PMR, 2) proposer et développer un algorithme d'optimisation locale basé sur la structure Voronoi 3D pour le déploiement de capteurs dans l'environnement intérieur 3D et 3) développer un algorithme d'optimisation destiné au déploiement d'un réseau de capteurs multi-types dans l'environnement intérieur afin d'aider la mobilité des PMR.

Le but de cette recherche était d'améliorer le processus de déploiement des capteurs en proposant une approche d'optimisation qui peut prendre en compte localement les informations sur la lisibilité de l'environnement, la proximité des capteurs et les éléments environnementaux qui auraient un impact sur ce processus. De plus, notre approche d'optimisation propose différentes configurations de déploiement de capteurs en fonction des différentes caractéristiques des capteurs utilisés. À titre d'exemple, des modèles réalistes de capteurs incluant des caméras et des Bluetooth ont été proposés et intégrés à l'estimation de la couverture des réseaux de capteurs dans le cadre de nos expérimentations. Les principaux objectifs et perspectives sont détaillés dans les chapitres 3, 4 et 5 comme les différents articles publiés ou soumis à des revues scientifiques. Par conséquent, le résumé des contributions de cette thèse est présenté dans les sous-sections suivantes.

6.2.1. Proposition d'un nouveau concept de lisibilité de l'environnement intérieur étendu pour les PMR

Il a été démontré au chapitre 3 que les facteurs personnels et environnementaux ont un impact sur la lisibilité de l'environnement intérieur. En effet, nous avons argumenté que les PMR perçoivent différemment les éléments environnementaux tels que les ascenseurs et les marches des escaliers lors de leur mobilité. Avec cette vision, nous avons proposé un nouveau cadre conceptuel pour la lisibilité des PMR inspiré du modèle PPH et de la notion d'affordance de Gibson pour mettre en évidence les différentes interactions entre une personne et son environnement. De plus, nous avons argumenté que la carte cognitive d'une personne est construite sur la base du cadre sens, plan et acte de l'expérience passée qui définissent la lisibilité afin que la mobilité soit bien supportée. Pour la personnalisation de l'évaluation de la lisibilité, nous avons utilisé le niveau de confiance d'une personne quant à sa capacité d'utiliser les facilitateurs et les obstacles. Ainsi, le concept de l'accessibilité et la présence des différents facilitateurs et obstacles ont été intégrés à d'autres facteurs tels que l'accès visuel, le niveau de connectivité et la complexité de la configuration des composants d'un bâtiment pour l'estimation de la lisibilité d'un environnement intérieur pour les PMR.

6.2.2. Proposition et implémentation d'un nouvel algorithme d'optimisation locale pour le déploiement de capteurs dans un environnement intérieur complexe 3D

La principale contribution du chapitre 4 a été l'intégration du modèle IndoorGML et de la structure de données Voronoi 3D pour proposer un algorithme d'optimisation locale pour le déploiement optimal d'un réseau de capteurs dans un environnement intérieur. Il a également été démontré que les informations géométriques et topologiques sur la structure du bâtiment et les paramètres des capteurs et leurs interactions améliorent la performance de l'algorithme de déploiement des capteurs et nous donnent une estimation plus réaliste de la couverture spatiale du réseau. De plus, il a été démontré que le modèle IndoorGML permet la gestion plus efficace du déploiement des capteurs sur les murs ou les plafonds. De plus, dans l'approche proposée, la surface du plancher a été considérée comme la zone de cible à couvrir par le réseau et l'estimation de la couverture a été réalisée en tenant compte de la présence des obstacles dans l'environnement intérieur. Le processus de déploiement des capteurs a été défini localement pour déplacer un certain nombre de capteurs de manière itérative en fonction des interactions locales entre les capteurs et les éléments environnementaux, tels que les obstacles, afin de minimiser leurs impacts sur la couverture du réseau. Le principal avantage de l'algorithme d'optimisation proposé est sa flexibilité et sa capacité à prendre en compte les différents niveaux de complexité de l'environnement dans le processus d'optimisation de la couverture du réseau.

6.2.3. Développement d'un nouvel algorithme d'optimisation de déploiement d'un réseau de capteurs multi-types pour aider à la mobilité des PMR dans des environnements intérieurs

La plupart des algorithmes d'optimisation ne prennent pas en compte les spécificités du domaine d'application dans le processus du déploiement de capteurs. Cependant, ils sont simplifiés par certains contextes qui n'ont pas priorité sur les places des capteurs dans le processus de déploiement. La contribution principale de cette partie de la thèse a été d'améliorer l'algorithme d'optimisation locale proposé dans le chapitre 4 afin de mieux considérer les spécificités de la mobilité des PMR dans le processus d'optimisation des réseaux de capteurs. Nous avons donc proposé l'intégration de l'information sur la lisibilité de l'espace dans le processus de déploiement des capteurs afin de mieux appuyer la mobilité des PMR. Pour ce faire, un nouvel algorithme été proposé basé sur l'intégration des informations sur l'environnement intérieur, du réseau de capteurs et de la lisibilité de l'environnement selon la perception des PMR lors de leur mobilité. De ce fait, une nouvelle stratégie a été proposée pour l'utilisation des capteurs multi-types (caméra avec champ de détection plus élevé et capteur Bluetooth avec champ de détection plus faible) pour aider la mobilité des PMR. Dans l'estimation de la couverture, en plus de l'intégration de la couche de lisibilité, les modèles probabilistes de la caméra et du capteur Bluetooth ont été appliqués dans l'estimation de la couverture, ce qui permet d'avoir une estimation plus réaliste de la couverture.

6.3. Perspectives de recherche et travaux futurs

La méthodologie présentée dans cette recherche a ouvert plusieurs nouvelles voies de recherche pour le développement des environnements intelligents et inclusifs dans le contexte du développement des aides pour améliorer la mobilité et la participation sociale des PMR. Voici quelques idées de perspectives de recherches futures.

Le déploiement des capteurs peut rencontrer des problèmes plus complexes lors de l'estimation de la couverture. Pour l'application de mobilité, les techniques de positionnement, telles que la triangulation, selon lesquelles chaque point doit être couvert par au moins trois capteurs (c.-à-d. problème de couverture k (Li and

Kao, 2010)) afin d'avoir une plus grande précision de la position de l'utilisateur. L'estimation de la couverture k peut être facilement développée en se la solution proposée au chapitre 4. Cependant, le développement d'une nouvelle stratégie de mouvement des capteurs pour pallier les problèmes de trous dans la couverture k pour un environnement intérieur reste une question ouverte et nécessite plus d'investigation.

La création de réseaux de capteurs ayant un champ de détection directionnelle limitée, comme des caméras directionnelles et des capteurs à ultrasons, sera important à faire. En effet, un réseau de capteurs pourrait être composé de plusieurs types de capteurs directionnels. La stratégie de rotation des capteurs en plus du mouvement pourrait être une solution dans de tels cas pour améliorer la qualité de couverture. Les réalisations de cette thèse apportent une nouvelle vision des stratégies de déploiement local permettant l'intégration de plus de diversité et d'hétérogénéité dans les réseaux de capteurs.

Nous pouvons également rencontrer d'autres problèmes, tels que la durée de vie de la batterie, le besoin de modéliser des informations obtenues par les capteurs et les limites dans la capacité de communication locale de ceux-ci. De plus, comment les stratégies d'optimisation locale peuvent-elles accommoder plusieurs objectifs? Par exemple, si tous les capteurs disponibles sont utilisés pour couvrir l'ensemble de la zone, comment s'arranger pour que la consommation d'énergie soit minimisée aussi? La combinaison d'objectifs multiples avec la complexité de l'environnement et la capacité limitée des capteurs nécessite une étude plus approfondie. Une solution pour cela pourrait être d'adapter la solution du Pareto Frontier (Tanabe & Ishibuchi, 2020) aux défis de déploiement des capteurs intérieurs, ce qui permettrait d'envisager un compromis entre différents objectifs (par exemple, coût, énergie, communication et couverture).

Cette thèse de doctorat a mené à une enquête sur l'évaluation personnalisée de la lisibilité des PMR dans l'environnement intérieur. Les tests des différents facteurs contributifs à l'évaluation de la lisibilité pour différents profils d'utilisateurs avec différents cas de test suscitent certaines préoccupations. Il sera important de mieux explorer les corrélations entre chaque facteur et les différents profils et de déterminer de manière rigoureuse le poids d'importance du calcul de la lisibilité pour chaque facteur influent, que ce soit l'accès visuel, la connectivité, la complexité de la disposition du bâtiment ou l'accessibilité.

Cette thèse a aussi permis une étude sur l'état statique des réseaux de capteurs, c'est-à-dire dans le cas où les capteurs ne sont pas automatiquement capables de se déplacer par eux-mêmes après leur placement. Il serait donc intéressant de mettre en œuvre une stratégie de déplacement visant l'optimisation locale sur des réseaux de capteurs mobiles afin que ces capteurs puissent se déplacer sur les plafonds et les murs pour atteindre la couverture optimale du réseau.

Malgré que la thèse a proposé les bases d'un cadre conceptuel de déploiement de capteurs en milieu intérieur pour assister les PMR lors de leur mobilité, en plus des capteurs de suivi de l'utilisateur, il existe des actionneurs (c.-à-d., *actuators* en anglais) qui peuvent être déployés de manière omniprésente dans l'environnement intérieur pour informer les utilisateurs des chemins accessibles et optimaux. Par exemple, des panneaux dynamiques (les écrans) peuvent être déployés dans des endroits intérieurs où les personnes ont le plus besoin d'aide lors de leur tâche de mobilité. La combinaison d'actionneurs et des capteurs apporte de nouveaux défis d'optimisation.

Enfin, cette thèse a été réalisée pour aider la mobilité des PMR, spécifiquement, les personnes utilisatrices d'un fauteuil roulant manuel. Cependant, pour les autres personnes à mobilité réduite, dont celles qui auront diverses difficultés telles celles de nature visuelle, auditive, cognitive, etc., le type de capteurs et d'actionneurs ainsi que leur déploiement dans l'environnement pourraient être modifiés en fonction du profil de la personne. Comprendre leurs besoins au cours de leur mobilité nous donnerait les informations appropriées pour être en mesure de re-concevoir l'environnement pour l'obtention d'un meilleur environnement intelligent et interactif. Considérer ces catégories et comprendre les types de profils et les enjeux qui y sont reliés nous amènerait à faire plus d'efforts afin de concilier les caractéristiques pertinentes et de mieux nous adapter à ces personnes à mobilité réduite.

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