Robot Localization Methods

Subjects: Robotics

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Robots are starting to be used on construction sites to perform various tasks. Robots utilizing only geometric information for localization within a construction site may not be able to localize correctly due to the fact the ongoing site does not resemble yet the architectural plans. Semantic information can help improve the localization but still can suffer inaccuracies due to large deviation of the robot pose estimate from its actual estimate and similar semantic information in case of repetitive environments.

localization SLAM Building Information Modelling (BIM)

1. Introduction

Robots are starting to be used on construction sites to perform various tasks such as autonomous data capturing to continuously monitor the evolution of the construction site, while construction environments are challenging because of their dynamic nature, as they can change significantly over a span of a few days, they have some features that are common in most of them, for example, walls, rooms, or pillars. Moreover, many companies are now integrating digital tools such as Building Information Modelling (BIM) [1] in their project design and execution phases. BIM contains geometric, semantic, topological, and physical information about each and every element of the building. Such crucial information is invaluable for a robot, which can use this knowledge for localization and understanding the construction site around it. Nevertheless, nowadays robots are unable to exploit the power of these digital plans. When they navigate in the environment, they either build their internal maps from scratch, which makes it difficult for them to know where they are, or they require fiducial markers to localize properly.

Most of the ongoing construction sites can be well represented using walls and rooms, to provide the robot with pre-existing knowledge of the environment. Robots utilizing only geometric information for localization within a construction site may not be able to localize correctly due to the fact the ongoing site does not resemble yet the architectural plans. Semantic information can help improve the localization but still can suffer inaccuracies due to large deviation of the robot pose estimate from its actual estimate and similar semantic information in case of repetitive environments. Thus, research is still required to combine the complete geometric, semantic, and topological information provided by the BIM models, to robustly localize a robot within an ongoing construction environment.

2. Global Localization

Global localization involves determining the position of a robot on a map that is already known. It is typically done in two steps. The first step is initial localization, which involves matching sensor readings to the map. This is sometimes called *the kidnapped robot prolem* [2], *re-localization* [3], or *place recognition* [4]. Multiple sensor modalities, including LiDAR [5], monocular [6], and stereo [7] cameras, can be employed for such tasks. One of the initial studies in this area was conducted by Fox et al. [8], who utilized a Markov model to update the probability distribution over potential locations in the environment based on sensor readings. Another method proposed by [9], called Monte Carlo Localization (MCL), models the robot state as a group of particles randomly sampled from the probability density function. MCL has been found to be highly effective in various situations [10][11][12][13]. Koide et al. [14] proposed global localization using 3d LiDAR measurements based on an Unscented Kalman Filter (UKF).

Alternative methods such as [15][16][17] utilize the extraction and matching of local point cloud descriptors. Key-point-based approaches face limitations due to the restricted uniqueness of local structures in LiDAR data. Nevertheless, they have gained traction as a substitute for those based on scan matching, attracting significant interest from the research community in recent years [18][19]. Learning-based localization has also shown promise in recent research. One example is SegMap, as presented in [20], which employs a distinct map representation for localization by extracting segments from 3D point clouds.

3. Architectural Plans Based Localization

In robotics use of 2D CAD-based models is very common to generate a 2D map of the environment and to localize a robot using the on-board range sensors [21][22]. Ref. [23] utilizes a monocular system to localize the robot in the 2D floor plans extracting the room layout edges. Refs. [24][25] incorporate semantic textual cues into the 2D floor plans to further improve the localization accuracy.

BIM on the other hand provides additional semantic and topological information as compared to 2D CAD plans which can be exploited to improve the planning and localization of mobile robots. Authors in [26][27][28] utilize BIM information for extracting 3D maps utilized by path-planner but do not include this information for robot localization. Authors in [29] only present a small case study localizing the robot through image matching between real images and images from BIM plans, but only restricted to a certain perspective. Ref. [30] present an approach to extracting information from BIM, splitting it into different floor levels, and then converting it to a relevant format used by a state-of-the-art pose-graph SLAM algorithm. Since the pose-graph algorithm cannot take as input an entire 3D mesh of the area, the authors have to create an additional module to generate trajectories within the mesh storing pose and sensor data at different intervals to later input it the SLAM for localization. Whereas in [31], authors present a case study converting BIM into 3D meshes at different floor levels and using a simple Iterative Closest Point (ICP) algorithm to localize the robot, thus depending highly on the metric ICP algorithm for convergence, which can show inaccuracies if an on-going construction site does not yet resemble the BIM plans. Compared to previous approaches, ref. [32] extract semantic information in addition to geometric information from the BIM plans to localize the robot using an on-board 2D LiDAR and pose-graph optimization, but the authors do not consider additional topological information connecting different walls to a room, etc.

4. Scene Graph Based Localization

Scene graphs are emerging research to represent the scene in several geometric, semantic, and topological dimensions [33][34][35][36][37]. *S-Graphs* [38] is a real-time optimizable hierarchical scene graph that represents the environment in geometric, semantic, and topological dimensions. *S-Graphs* is capable of not only representing the environment as a scene graph but also simultaneously optimizing all the elements within it including the robot pose. All of these methods need the robot to navigate the environment in order to create the scene graphs, which means they need to know the starting point of the robot beforehand. They lack the capability of performing global localization. Some methods have also emerged exploiting scene graphs for localization such as [39][40][41] performing graph-based localization utilizing spatial information between the neighboring landmarks. Similarly, authors in [42] create a global topological semantic map of the environment and later use similarity between semantic scene graphs to localize the robot. Ref. [43] combine traditional 3D object alignment with graph-based matching to perform global localization in small-sized areas such as rooms.

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