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Online topological map building and qualitative localization in large-scale environment

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ABSTRACT

A novel topological map representation as well as an online map construction approach is presented in this paper. By virtue of the topological map whose nodes are represented with the free beams of the laser range finder together with the visual scale-invariant features, the mobile robot can autonomously navigate in unknown, large-scale and indoor environments. Different from the traditional navigation methods that rely on precise global localization, the robot locates itself qualitatively by location recognition rather than calculating its global pose in the world reference frame. By combining the reactive navigational method, Beam Curvature Method (BCM), with the topological map, a smooth, real-time navigation without precise localization can be realized.

1. Introduction

Sensor based exploration for mobile robot in unknown environments has a variety of potential applications in such diverse areas as forestry, nuclear reactors, environmental disasters, industry, and offices [1]. Tasks in these environments are often hazardous to humans, remotely located, or tedious to perform. Simultaneous localization and mapping (SLAM) that combines the techniques of mapping and localization and exploration that combines the techniques of mapping and path planning have been extensively researched by the robotics community in the last decade. Since map representation and construction play an important role in autonomous navigation, a good map should not only be more convenient for construction and maintenance, but also be more suitable for map based localization and path planning in large-scale environments.

The most common representations of the world model in mobile robotics have been grouped into metric maps, topological maps and hybrid models that combine both metric and topological information [2].

A metric map, including the grid based approaches and the geometric approaches, represents the environment according to the absolute position of the objects. The grid based approaches [3] are adequate for local navigation like obstacle avoidance and map based localization. However, their application has been limited since they have a high computational cost in feature matching. In the geometric approaches [4], the environment is represented with geometric beacons and the position of the robot is estimated by matching the sensed features against the world model. Those algorithms were vulnerable to sensing errors and environmental uncertainties in the past because they rely on precise metrical information. Recent researches on the reduction of computation cost and the techniques of mapping and localization have remedied such limitations to some extent. For instance, methods such as fastSLAM and Roa-Blackwellian EKF [5,6] are quite capable of handling noise observations, kidnapped robot solutions and environmental uncertainties robustly.

In contrast, topological approaches usually represent the world model in graphs and are known to be robust to the fragility of purely geometrical methods [7,8]. Moreover, the elements of the topological map are strongly related to the semantics of the environments while the other two maps put more emphasis on geometrical information. So the topological map is more capable than the others in managing reactive behaviors especially in large-scale environments.

Though a topological map mimics the way how a human memorizes a map, it may lack the details of an environment. To solve these problems, a hybrid map combining the topological and the metric paradigm [9,10] has shown that positive characteristics of both can be integrated to compensate for the weakness of each single approach.

However, one factor that impedes the application of topological maps is the lack of uniform semantics associated with these

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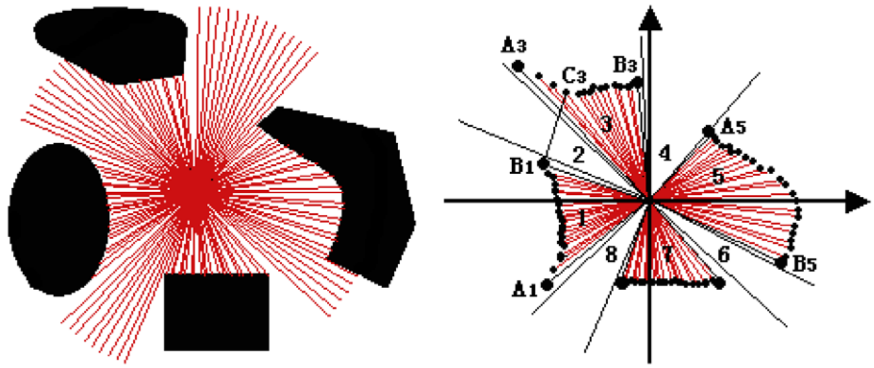

(a) The detection of the obstacle by laser range finder.

(b) The classification of beam.

Fig. 1. Representing the world model with beams.

graphs. For instance, Kuipers [11] represents nodes with places characterized by sensor data, and represent arcs with paths between places characterized by control strategies. In contrast, the maps defined by Thrun [12] are obtained by partitioning a probabilistic occupancy grid into regions separated by narrow passages according to a measure of local clearance. Since different definition usually means a different topological architecture, it is difficult for a robot, even for an human operator, to construct a topological map online during the exploration in large-scale environments. Fabrizi [13] extracts topological information from the grid map by considering the grid map as a gray-level image. They use fuzzy mathematical morphology to gather information about the shape of the empty space represented in the grid map, and fuzzy digital topology to extract the topological structure of this information. This hierarchical approach still has the problem of large memory requirement involved in a grid map. As an alternative to this approach, the direct topological map building using the generalized Voronoi graph (GVG) was proposed in [13,14]. GVG is formed by a set of points equidistant to the obstacles in the n-dimensional space. Using this approach the robot can collect topological information with low-cost sonar sensors, but in this case the robot has to move on the GVG edges sufficiently, and some types of nodes and edges such as weak meet points and boundary edges tend to be extracted due to sensor noise and environmental complexity. GVG is sensitive to the dynamic, large-scale environments with arbitrarily shaped obstacles and needs long computation time for node extraction and matching. Tae-Bum [15] proposed a thinning method to build a topological map from a binary grid map. This method needs much simpler computation than that using a Voronoi diagram. However, thinning method need a existed grid map as its basis, which impede its application in online map construction.

Another factor that limits the application of the topological map is the online detection and recognition of the topological nodes. A variety of artificial landmarks such as ultrasonic beacons, reflecting tape, or visual patterns, allows fast and stable recognition of the specific location despite the fact that there often exist no artificial landmarks available in unknown environments. Many researchers manage to extract the distinctive features that are unaffected by nearby clutter, partial occlusion or partial environment variation. Some candidate feature types, such as line segments, groupings of edges, eigenspace matching and Harris corner detector have been proposed and explored. It has been demonstrated by many researchers that the scale-invariant feature transform (SIFT) [16,17] can produce the features those are invariant to image scaling, translation, rotation and partially invariant to illumination changes and affine or 3D projection. So we use Lowe's scale-invariant features together with laser's beam features to represent the node so that it can be detected and recognized easily.

We also use a reactive navigational method, BCM, to extract the topological nodes directly from the information acquired by a 360° laser range finder [18,19]. Without building a grid map beforehand, our approach requires less computation than any other map building method mentioned above.

The remainder of this paper is organized as follows. Section 2 introduces the online topological map building with BCM. The improvements on scale-invariant features transform has been given in Section 3. Some experimental results of topological map building and autonomous navigation are summarized in Section 4. Finally, conclusions and discussions are given in Section 5.

2. Building a topological map online with BCM

In our previous work on local obstacle avoidance, the discrete point acquired by laser range finder was first divided into several candidate beams in terms of the data clustering method. Subsequently BCM can select the best beam by maximizing an objective function to produce the linear and angular velocity commands.

We divide all the beams, as is shown in Fig. 1, into two categories: the block beam and the free beam. The block beam is the beam that associates with an obstacle, while the free beam is the beam that does not comprise an obstacle or the obstacle is beyond the predefined detecting range of the sensors. It is obvious that beam 1, 3, 5 and 7 belong to the first type, while beam 2, 4, 6 and 8 belong to the second one. We denote the beam as a quadruple, $B(\rho_{i1}, \rho_{i2}, d_i, w_i)$, where ρ_{i1}, ρ_{i2} are the orientations of corresponding sensors in the robot's local reference frame; d_i is the minimum length from the ith beam to the robot; w_i is the width of the ith beam calculated by Eq. (1). As is shown in Eq. (1), $A_{i-1,j}$ is the jth point in the $(i-1)$th obstacle; $B_{i+1,k}$ is the kth point in the $(i+1)$th obstacle. Eq. (1) indicates that the width of the free beam is the minimum distance between the left and right neighboring block beams. It is obvious that in Fig. 1(b), the width of the 2nd beam is denoted by $|B_1C_3|$.

$$w_i = \begin{cases} 2d_i \tan\left(\dfrac{\rho_{i2}-\rho_{i1}}{2}\right) & \text{block beam} \\ \min\limits_{j,k}(|A_{i-1,j}B_{i+1,k}|) & \text{free beam} \end{cases} \qquad i = 1, 2, \ldots, n. \quad (1)$$

2.1. Definition of the node

In our topological map, either a space that has one opening or the intersection between different routes, i.e. a doorway, the corner of a corridor will be regarded as a topological node. The arcs are represented with the paths between different nodes, characterized by the distance and the orientation.