Effizientes Lernen Metrischer und Topologischer Karten mit Autonomen Servicerobotern

Efficiently Learning Metric and Topological Maps with Autonomous Service Robots

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Keywords: SLAM, metric map, topological map, particle filter, semantic information

Schlagworte: SLAM, metrische Karten, topologische Karten, Partkelfilter, semantische Informationen

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Abstract

Models of the environment are needed for a wide range of robotic applications, from search and rescue to automated vacuum cleaning. Learning maps has therefore been a major research focus in the robotics community over the last decades. In general, one distinguishes between metric and topological maps. Metric maps model the environment based on grids or geometric representations whereas topological maps model the structure of the environment using a graph.

The contribution of this paper is an approach that learns a metric as well as a topological map based on laser range data obtained with a mobile robot. Our approach consists of two steps. First, the robots solves the simultaneous localization and mapping problem using an efficient probabilistic filtering technique. In a second step, it acquires semantic information about the environment using machine learning techniques. This semantic information allows the robot to distinguish between different types of places like, e.g., corridors or rooms. This enables the robot to construct annotated metric as well as topological maps of the environment. All techniques have been implemented and thoroughly tested using real mobile robot in a variety of environments.

Zusammenfassung

Umgebungsmodelle sind die Grundlage für viele Applikationen innerhalb der mobilen Robotik wie beispielsweise Rettungsaufgaben oder autonomes Staubsaugen. Techniken zum Bauen von Karten mit mobilen Robotern werden daher seit vielen Jahren intensiv untersucht. Meist unterscheidet man hier zwischen metrischen und topologischen Karten. Metrische Modelle verwenden geometrische Darstellungen, wohingegen topologische Karten typischerweise durch Graphen repräsentiert werden.

Der Beitrag dieser Arbeit besteht in einem Verfahren zum Erstellen von metrischen wie auch topologischen Karten, basierend auf Daten, die mittels Abstandssensoren aufgenommen wurden. Unser Ansatz basiert auf zwei Schritten. Zuerst wird das sogenannte simultane Lokalisierungs- und Kartenbauproblem mit Hilfe wahrscheinlichkeitstheoretischer Filtertechniken gelöst. Im zweiten Schritt schätzt unser Verfahren semantische Informationen über Orte in der Umgebung. Diese Technik erlaubt es einem Roboter beispielsweise zu entscheiden, ob dieser sich gerade in einem Raum, einem Türrahmen oder in einem Korridor befindet. Dadurch kann der Roboter die metrische Karte annotieren und somit die Topologie schätzen. Um Klassifikationsfehler zu minimieren, verwenden wir eine probabilistische Relaxationsmethode. Das hier vorgestellte Verfahren wurde implementiert und mit Hilfe echten mobilen Robotern intensiv getestet und evaluiert.

1 Introduction

The problem of learning maps is one of the fundamental problems in mobile robotics. Models are needed for a series of applications like transportation, cleaning, rescue, localization, and various other service tasks. Learning maps has therefore been a major research issue in the robotics community over the last decades.

Typically, one distinguishes between the type of model the mapping approach learns: metric or topological maps. Metric maps like, for example, occupancy, feature, or geometric maps model the objects observed by the sensor. However, for different robotic tasks the robot can improve its capabilities or performance when sematic or topological information is available. In contrast to metric maps, topological maps model the structure of the environment using a graph in which the different places in the environment are represented by nodes.Topological maps are quite popular in the robotics community because they are believed to be cognitively more adequate. Compared to metric maps, they can be stored in a compact manner and can facilitate the communication with the users.

While most other mapping approaches address metric or topological map learning, we focus in this paper on constructing a metric as well as a topological model of the environment. Our approach consists of two steps. In the first one, we apply a highly efficient particle filter to solve the *simultaneous localization and mapping* (SLAM) problem. This step is based on grid maps and eliminates the pose uncertainty of the robot. In the second step, we use the grid resulting from the first step in order to learn the topology. Our technique estimates semantic information about local areas using supervised learning. It furthermore applies probabilistic relaxation labeling to smooth the semantic labels and then identifies distinct places based on that data. This allows a mobile robot to learn accurate metric models of the environment while at the same time constructing a consistent topological map.

The remainder of this paper describe the two steps of our algorithm in the next sections. The first step explains our Rao-Blackwellized particle filter is applied to construct a metric grid map. Based on this result, Section 3 describes the second step of our technique which is the extraction of the topological information.

2 Step 1: Efficient Metric Mapping

This section describes the first step of our mapping approach. The goal is to eliminate the pose uncertainty of the mobile robot and to obtain a consistent grid representation. According to Murphy [16], the key idea of the Rao-Blackwellized particle filter for SLAM is to estimate the joint posterior $p(x_{1:t}, m \mid z_{1:t}, u_{1:t-1})$ about the map m and the trajectory $x_{1:t} = x_1, \ldots, x_t$ of the robot. This estimation is performed given the observations $z_{1:t} = z_1, \ldots, z_t$ and the odometry measurements $u_{1:t-1} = u_1, \ldots, u_{t-1}$ obtained by the mobile robot as

$$p(x_{1:t}, m \mid z_{1:t}, u_{1:t-1}) = p(m \mid x_{1:t}, z_{1:t}) \cdot \cdot p(x_{1:t} \mid z_{1:t}, u_{1:t-1}).$$

This factorization allows us to first estimate only the trajectory of the robot and then to compute the map given that trajectory.

The posterior over maps $p(m \mid x_{1:t}, z_{1:t})$ can be computed analytically using “mapping with known poses” since $x_{1:t}$ and $z_{1:t}$ are known. To estimate the posterior $p(x_{1:t} \mid z_{1:t}, u_{1:t-1})$ over the potential trajectories, one can apply a particle filter in which each particle represents a potential trajectory of the robot. Furthermore, an individual map is associated with each sample.

One of the most common particle filtering algorithms is the sampling importance resampling (SIR) filter. A SIR filter for mapping can be summarized by four steps: sampling, importance weighting, resampling and map estimation [4]. In the sampling step, the next generation of particles is obtained from the so-called proposal distribution. In the importance weighting step an individual weight is assigned to each particle according to the importance sampling principle. Particles are then drawn with replacement proportional to their importance weight in the resampling step. Finally, for each particle, the corresponding map estimate is computed based on the trajectory of that sample and the history of observations.

The general framework for mapping with Rao-Blackwellized particle filters leaves open how the proposal distribution is computed. In general, the filter produces more accurate results the closer the proposal approximates the target distribution. The target distribution, however, is typically not available in a closed form solution suitable for sampling. In our case, the target distribution is given by

$$\begin{aligned} p(x_{1:t} \mid z_{1:t}, u_{1:t-1}) = \\ \eta \cdot p(z_t \mid m_{t-1}^{(i)}, x_t) \cdot \\ \cdot p(x_t \mid x_{t-1}, u_{t-1}) \cdot \\ \cdot p(x_{1:t-1} \mid z_{1:t-1}, u_{1:t-2}), \end{aligned}$$

where η is a normalizing constant resulting from Bayes' rule.

Our approach uses the laser range observations of the robot in order to approximate the target as close as possible while being able to efficiently sample from that distribution. The advantage of this approach lies in the fact that the laser range observations are typically affected by significantly less noise compared to the odometry of the robot (which is used as the proposal in classical particle filter applications). This fact is illustrated in Figure 1. Since the resulting distribution is given by the product of the motion and the observation model, one can restrict the search to areas of high likelihood (called meaningful area $L^{(i)}$ in Figure 1). We consider both components of the proposal, the observation likelihood and the motion model within the meaningful interval $L^{(i)}$ and we locally approximate the posterior $p(x_t \mid m_{t-1}^{(i)}, x_{t-1}^{(i)}, z_t, u_{t-1})$ around the maximum of the likelihood function reported by a scan registration procedure (see [5] for more details).

A further aspect that has a major influence on the performance of a particle filter is the resampling step. During resampling, particles with a low importance weight $w^{(i)}$ are typically replaced by samples with a high weight. On the one hand, resampling is necessary since only a finite number of particles are used to approximate the target distribution. On the other hand, the resampling step can remove good samples from the filter which can lead to particle impoverishment. Accordingly, it is important to find a criterion for deciding when to perform the resampling step. Following the formulation of Doucet *et al.* [2], we calculate the so-called effective sample size to estimate how well the current particle set represents the target posterior as

$$N_{\text{eff}} = \frac{1}{\sum_{i=1}^{N} (\tilde{w}^{(i)})^2},$$

where $\tilde{w}^{(i)}$ refers to the normalized weight of particle i.

Since N_{eff} can be regarded as a measure of the dispersion of the importance weights, it is a useful measure to evaluate how well the particle set approximates the target posterior. We resample each time N_{eff} drops below the threshold of $N/2$ where N is the number of particles. In extensive experiments, we found that this approach drastically reduces the risk of replacing good particles.

3 Step 2: Estimating the Topology

In the previous section, we presented a way for learning accurate metric maps of the environment. The results of this first step are now used to build a topological representation of the environment. The complete process is divided into two steps. First, the semantic classification of each unoccupied cell is determined. Second, from the resulting labeling we construct a graph whose nodes correspond to the regions of identically labeled poses and whose edges represent the connections between them.

For each unoccupied cell of the grid map, our approach first determines its semantic class (room, corridor, doorway). This is achieved by simulating a range scan given the sensor is located in that particular cell and then classifying this scan into one of the classes. The classification is done using a sequence of classifiers learned with the AdaBoost algorithm. Each classifier in the sequence is learned in a supervised fashion from examples represented by a vector of simple geometric features that are extracted from range scans simulated in different, previously labeled maps of standard environments [12]. During the learning process, AdaBoost selects the best features and combines them to a strong classifier by weighted majority voting. Additionally, we calculate a confidence value for the output classification Because this approach distinguishes between only two classes, we arrange the classifiers into a decision list to create a multi-class classifier [19].

Once we have classified each free cell into one of the semantic class, we apply a smoothing process called probabilistic relaxation labeling to eliminate errors in the labeling. This method takes into account the labeling of neighboring cells to change or maintain the label of a concrete cell. The approach calculates prior probabilities about the relation between neighboring labels using already labeled environments. The classification of each cell is then updated in aN iterative way using these priors together with the neighborhood information [11].

After the smoothing procedure, we extract regions composed of groups of 8-connected cells in the grid map. Finally, a topological graph is constructed in which each node represents a complete region and each edge represents a connection between them. Additionally, we apply a heuristic region correction to the topological map to increase the classification rate [11].

4 Experiments

The approach described above has been implemented and tested using real robots and datasets gathered with real robots. We first present the results of our SLAM approach and then illustrate how topology of the environment.

A map of the Intel Research Lab is depicted in the left image of Figure 2 with a size of 28 *m* by 28 *m*. The dataset has been recorded with a Pioneer II robot equipped with a SICK laser range finder. To successfully correct this dataset, our algorithm needed only 15 particles. As can be seen in the right image of Figure 2, the quality of the final map is so high that the map can be magnified up to 1 *cm* of resolution without showing any significant errors. In addition to the Intel dataset, we also corrected other datasets which can be found on the web [18].

In order to measure the improvement in terms of the number of particles, we compared the performance of our system using the informed proposal distribution to the approach done by Hähnel *et al.* [6]. It turns out that in all of the cases, the number of particles required by our approach was approximately one order of magnitude smaller than the one required by the other approach. Moreover, the resulting maps are better due to our improved sampling process that takes the last reading into account. A more detailed discussion on our approach can be found in [5].

Based on the results of the Rao-Blackwellized particle filter shown in Figure 2, we now construct the topological map. We first trainned a general classifier for detecting rooms, corridors and doorways. The training set was composed of two different maps of the University of Freiburg in which the different places were manually labeled. Then, we applied the classification and topological extraction method of Section 3. As depicted in Figure 3, the resulting topology represents the environment in a good way. The main error in the topology are missing doorways, since the doors in this environment look different to the environment in which the classifiers. Additional experiments can be found in [11].

5 Related Work

Mapping techniques for mobile robots can be roughly classified according to the map representation and the underlying estimation technique.

In a work by Murphy, Doucet, and colleagues [1, 16], Rao-Blackwellized particle filters (RBPF) have been introduced as an effective means to solve the SLAM problem. Each particle in a RBPF represents a possible robot trajectory and a map. The framework has been subsequently extended by Montemerlo et al. [14, 15] for approaching the SLAM problem with landmark maps. To learn accurate grid maps, RBPFs have been used by Eliazar and Parr [3] and Hähnel *et al.* [6]. The SLAM technique described in Section 2 is an improvement of the algorithm proposed by Hähnel *et al.* [6]. The computation of the proposal distribution is done in a similar way as in FastSLAM-2 presented by Montemerlo *et al.* [14]. In contrast to FastSLAM-2, our approach does not rely on predefined landmarks and uses raw laser range finder data to acquire accurate grid maps.

In the past, different algorithms for creating topological maps have been proposed. Kuipers and Byun [9] extract distinctive points in the map. Kortenkamp and Weymouth [7] fuse the information obtained with vision and ultrasound sensors to determine topologically relevant places. Shatkey and Kaelbling [17] apply a HMM learning approach to learn topological maps. Additionally, Kuipers and Beeson [8] apply different learning algorithms to calculate topological maps of environments. These approaches only identify points in the map that have special properties but they do not include semantic meaning.

In the context of learning topological map from noisy data, Modayil *et al.* [13] presented a technique which combines metrical SLAM with topological SLAM. Similar ideas have been realized by Lisien *et al.* [10], which introduce a hierarchical map in the context of SLAM.

With respect to place classification, our approach is an extention of our previous work [12]. We additionally use a probabilistic variant of the classifier and apply a probabilistic relaxation labeling to incorporate similarity constraints between neighboring points and to eliminate false classifications.

6 Conclusion

In this paper, we presented a method to learn accurate metric as well as topological maps under uncertainty. We described our algorithm that consists of two consecutive steps. First, it applies a Rao-Blackwellized particle filter to solve the SLAM problem and to create metric occupancy grid maps. We compute a highly accurate proposal distribution based on the observation likelihood of the most recent sensor information, the odometry, and a scan-matching process. In the second step, we extract semantic place labels from the metric model for categorizing places into semantic classes such as rooms, doorways, and corridors. We apply a probabilistic relaxation process to reduce classification errors. We then extract regions and their connections which results in a topological representation of the environment. Our approach has been implemented and evaluated using real robots equipped with a laser range finder. The experiments demonstrate that our approach is well-suited to extract metric and topology from indoor environments.

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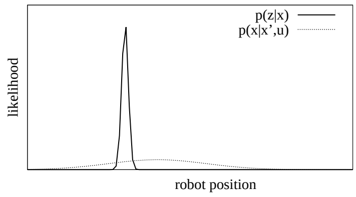

Abbildung 1: The two components of the target distribution. Within the interval $L^{(i)}$ the product of both functions is dominated by the observation likelihood, which is therefore well-suited to focus the proposal to the interval $L^{(i)}$.

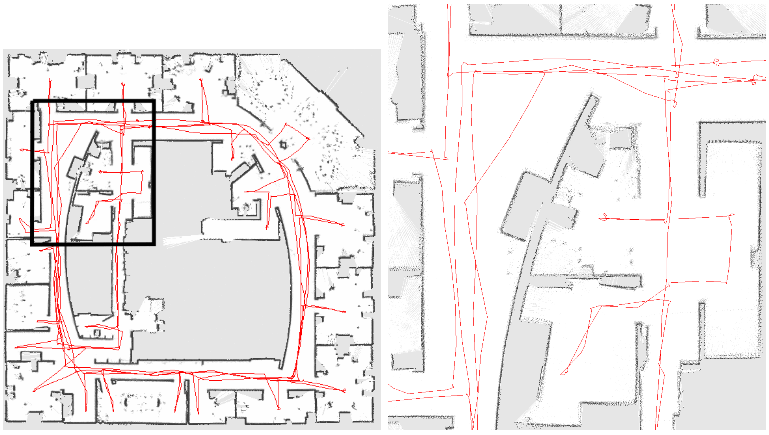

Abbildung 2: The Intel Research Lab. The robot starts in the upper part of the circular corridor, and runs several times around the loop, before entering the rooms. The left image depicts the resulting map generated with 15 particles. The right image shows a cut-out with 1 *cm* grid resolution to illustrate the accuracy of the map in the loop closure point.

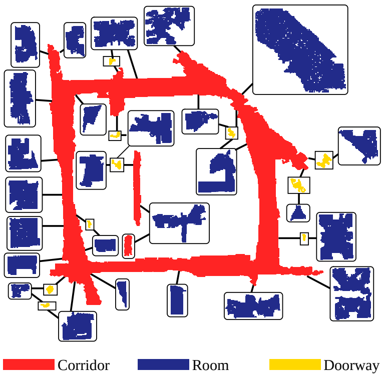

Abbildung 3: The topological map learned from the Intel Research Lab.