Chapter 6
Semantic Information in Exploration and Localization*

6.1 Introduction

The work presented in the previous chapters showed how to augment the representation of indoor environments using semantic information about places. In this chapter we describe how robots can use the intrinsic information of human-made environments to improve their actions. In particular, we apply the semantic labeling of places to two robotic tasks: multi-robot exploration, and localization. In both cases the performance of the robot increases when it takes into account the classification of its location.

Exploration and localization belong to the fundamental problems in mobile robotics [22]. In the exploration task a mobile robot is controlled in a way that maximizes the information about its environment. A typical goal in exploration consists of creating a map of a previously unseen environment. Moreover, the use of multiple robots is often suggested to have advantages over a single robot during exploration, since cooperating robots have the potential to accomplish a task faster than a single robot [7]. In the localization task, a mobile robot has to determine its pose relative to a map of a given environment.

In this chapter, we first present an approach to include semantic information about places to better distribute the robots in human-made environments during an exploration task. As we have seen in previous chapters, indoor environments constructed by humans contain structures like corridors, rooms or offices. Moreover, corridors are connected to several rooms and provide more branchings to new unexplored areas. The key idea is then to assign higher rewards to robots that first explore corridors. As a result, the overall completion time of an exploration task can be significantly reduced.

In a second approach, we use the semantic labeling to localize a robot in an indoor environment using the Monte Carlo localization approach [3]. The main idea here is to take as observation model the semantic classification of the current pose of the mobile robot.

* The work presented in this chapter originated from a collaboration with Cyrill Stachniss.
The rest of the chapter is organized as follows. The next section presents the approach for multi-robot exploration using semantic information. In Sect. 6.3, we introduce the Monte Carlo approach for localization using semantic labels. Section 6.4 presents experimental results. We discuss related work in Sect. 6.5. Finally, conclusions are presented in Sect. 6.6.

6.2 Multi-robot Exploration Using Semantic Information

In multi-robot exploration, a team of robots is distributed in a new environment with the objective of accumulating information to create a map. In this task, we are interested in finding good assignments of goal positions for the robots in the team. In our case, we assign target locations with the aim of minimizing the time needed to complete the exploration.

6.2.1 Classifying Target Locations

We assume that the knowledge about the environment is represented by an occupancy grid map. In this representation, target locations are found at the frontier between known and unknown areas [24]. As an example, Fig. 6.1(a) shows a map together with the frontiers detected there (dashed lines). For each of the frontiers, a target location is generated.

The goal now is to classify each potential target location into a semantic class. One possible solution to classify a target location is to simulate an observation at its position, and then classify this observation using the approach presented in Chap. 3. However, the target position is located at a frontier, which means that part of the neighboring areas are not known. Therefore, the laser observations simulated at frontier cells contain a significant number of maximum-range readings, which can lead to high missclassification rates.

To increase the classification rate in these cases, a short virtual trajectory to the desired goal location is generated. We then simulate laser range observations at different poses along this virtual trajectory using the partially known map. These poses

![Fig. 6.1](image)

(a) Frontier extraction  (b) Virtual trajectory

Fig. 6.1 (a) The image shows a situation in which a robot has extracted the frontiers of the occupancy grid map (dashed lines). Additionally, a target location is shown for one of the frontiers. (b) A virtual trajectory to the target is generated by the robot.