RG Mapping: Building Object-Oriented Representations of Structured Human Environments

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Abstract— **We present a new approach to mapping of indoor environments, where the environment structure in terms of regions and gateways is automatically extracted, while the robot explores. Objects, both in 2D and 3D, are modelled explicitly in those maps and allow for robust localization. We refer to those maps as object-oriented environment representations or region and gateway maps. RG mapping is capable of acquiring very compact, structured, and semantically annotated maps. We show that those maps can be built online and that they are extremely useful in plan-based control of autonomous robots as well as for robot-human interaction.**

I. INTRODUCTION

Many autonomous mobile service robots use maps, models of their environments, as resources to perform their tasks more reliably and efficiently. So far maps have mainly be employed for reliable and efficient navigation in the robot's operating environment. The most commonly used map representations for these purposes include probabilistic occupancy grid maps, maps that are sets of geometric primitives such as lines or planes, and topological maps that represent environments as graphs with landmarks as nodes and arcs labeled with control routines for navigating between neighboring landmarks. An excellent survey of mapping algorithms can be found in [9]. However, as autonomous service robots become more sophisticated and are to perform more complex tasks, new requirements for maps arise: maps must represent the structure of environments, including rooms, hallways, and doorways, and they must store the task-relevant objects in the environment.

The need for quick deployment of service robots also requires the robots to autonomously acquire maps of their new operating environments. Consequently, a number of techniques for the acquisition of environment maps of office buildings, museums, and other indoor environments have been developed [1], [11], [3]. While most recent mapping algorithms have been designed to acquire very accurate maps [4], [3], [10], [5], [7], little attention has been paid to extend these algorithms to acquire additional information about the environment or make the representation compact.

In this paper we describe ***RG*** mapping (***R***egion and ***G***ateway mapping) an autonomous robot mapping system that is capable of acquiring ***RG*** maps (***R***egion and ***G***ateway maps). RG mapping makes several important technical contributions to existing mapping techniques, in particular to Gutmann's scan matching [4]. First, RG mapping infers compact yet accurate line segment-based geometric descriptions. Because these 2D-line maps describe areas as a small number of line segments they yield smaller search spaces for generating object hypotheses. Second, RG maps capture hierarchical structures that are typically found in indoor environments such as office buildings and appartments. Third, RG maps store mission relevant objects in the environment. RG maps represent environments as a set of regions connected by gateways. [1] Regions are described compactly using a set of line segments. Regions also contain sets of object hypotheses, where we restrict ourselves to object classes that are rectangular, such as pictures, and objects that can be represented by bounding cuboids, such as desks. The gateways represent transitions between regions.

The remainder of the paper is organized as follows. The next section describes our map representation. After the map description we briefly sketch the mapping system. Finally, we conclude with experimental results and a discussion of ongoing work.

II. MAP REPRESENTATION

Since buildings, in particular office buildings, are designed to be functional, well-priced, and ef-

[1] In cognitive science similar maps have been proposed in the context of cognitive [2] and topological mapping [6].

Region	
in general	in particular
Metric 2D/3D data for sensor based localization	Map of 2D line segments
2D/3D Object hypotheses	2D/3D Rectangles; 2D Circle; (evt. Bounding Cubes)
Feature Vector for recognition/classifi cation	Bounding Rectangle; 1st, 2nd order moments; main axes; freespace
Characteristic measures	accuracy/completeness
Connected Gateways (as reference)	List of pointers to Gateways
List of Sub-Regions	not yet supported

Gateway	
in general	in particular
Characteristic features for detection, recognition and traversal observation	Gateway points; Crossing Points plus traversal direction
Class label	L/R-Turn, X/T-Junction, Narrow Passage, Open/Close-Transition
Adjacent regions (as reference)	List of pointers to regions
Metric 2D/3D data	not yet supported

TABLE I

SUMMARY OF THE FEATURES OF REGION & GATEWAY MAPS

ficient, they share salient design characteristics. They are structured into rooms that can be entered through doorways. Such regions are usually connected to other rooms and/or hallways. And hallways can be connected by L/R-Turns, X/T-Junctions etc. In this section we propose RG maps as a means of representing such structures.

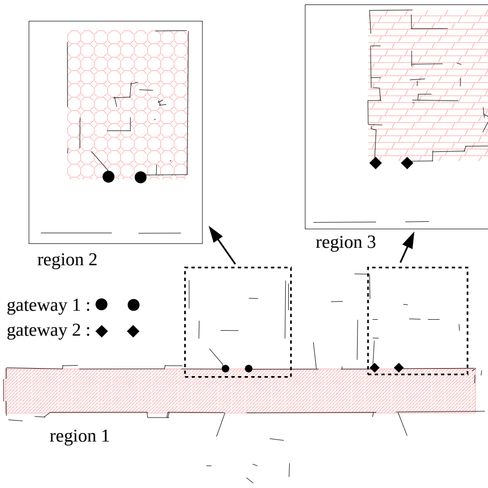

Fig. 1. Region & Gateway Map

Before we lay out our basic representational concepts let us first consider figure 1 to get an intuition of how office environments are represented as an RG map. The map shows three regions: region 1 to 3 connected by two gateways of type *Narrow Passage*. The regions are visualized through their geometric description, a set of line segments. Bounding boxes of the regions, the smallest rectangle containing all possible robot positions in the region, are indicated through the background fill patterns. Among other things, the geometric description is used to predict the laser scan that the robot should receive at a given location within the region. Note that the geometric description contains lines that are outside the region's bounding box. This is because these lines can be seen through the gateway and used for robot self-localization.

RG maps are tuples $\langle R, G \rangle$, where R denotes a set of regions and G is a set of gateways that represent the possible transitions between regions. A region has a compact geometric description (for now we use 2D-line segments), a bounding box, one or two main axes, a list of adjacent gateways, and a set of object hypotheses.

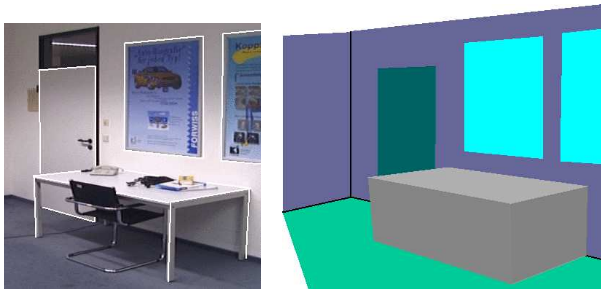

Fig. 2. Visual 3D landmarks (object hypotheses)

The geometric description of a region consists of a set of 2D lines that best match the received laser range data and odometry readings. The lines of a region produce a very compact and accurate line based local 2D-map. Regions are associated with a measure of accuracy that specifies how accurately the geometric description reflects the sensor data obtained in this region. Region representations also comprise a set of object hypotheses, which are subsets of 2D lines that might belong to the same object in 3D. This will be used as an initialization for camera based object recognition in future work. The key idea for such an approach is depicted in figure 2 and will be explained in more detail in the next section.

The second key component of our map representation are gateways. Gateways represent transitions from one region to another. In indoor environments several types can be distinguished, e.g. hallway T/L/X-junctions as well as narrow passages and changes from a rather narrow hallway into an open room, e.g. a lobby, see also figure 3. Gateways are specified by a class label, adjacent regions, traversal directions, crossing-points and gateway-points that can be used for detecting when a gateway is entered and left. A number of researchers including Kortenkamp [6], Youngblood [11] and Chown [2] have proposed gateways as first class objects in map representations. Table I summarizes all features of regions and gateways. Whereas "in general" refers to the more general description of features, "in particular" points out what has been implemented already or is currently worked on in the context of our mapping/navigation system.

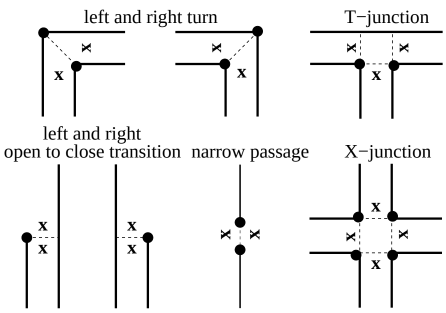

Fig. 3. gateways with crossing-points (×) and gateway-points (•)

III. Map Building

After having described RG maps, we will now turn to the question of how they can be acquired.

Figure 5 depicts the overview of the mapping and navigation system. Currently, we run the system on a B21 mobile robot from iRobot Corporation equipped with a 180 degree laser range finder that is mounted horizontally at a height of about forty centimeters facing to the front. The senor data is first synchronized with odometry readings to allow for fusing different measurements (laser, vision) within one map. Laser scan packets are then fed into the `ScanMapper` which alligns the scans using Gutmann and Konolige's Local Registration/Global Correlation (LRGC) algorithm [4]. The `Region & Gateway Mapping` module utilizes those scans to detect gateways and generate a compact map of 2D line segments. Furthermore it uses the data to calculate 2D object hypotheses (rectangle, circle) which can be used for global localization as well as for initializing image interpretation.

The path planning within a region can be easily performed using methods like voronoi-diagrams, mid-point path planning or steepest gradient. Globally, the trajectory can be planned utilizing a graph representation of the RG map and then applying roadmap planning. Localization within a region uses particle filter and scan matching. For global localization it is necessary to be able to recognize regions based on the before mentioned feature vector. Also an action history can be utilized to not consider all possible regions but only the most likely according to the path the robot has taken.

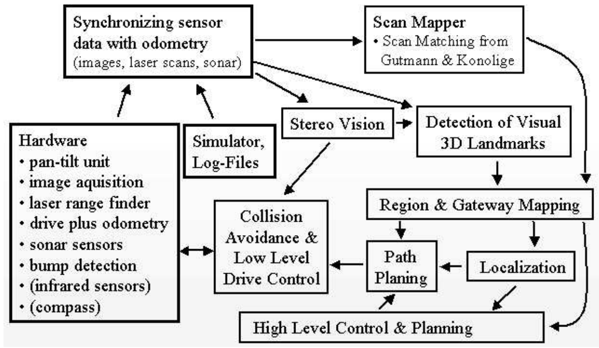

Fig. 5. Overview of the Mapping & Navigation System

Furthermore, the map initializes and supports the generation of 3D object hypotheses, which works as follows. First, we extract the room structure from the 2D-line set describing the region. That means estimating the position of the walls, which is similar to the before mentioned bounding rectangle for a region. The lines included in that rectangle are grouped into object hypotheses. For example, an office closet would have a rectangular outline. Such a description provides clues concerning depth irregularities, which can be correlated with 3D-data derived from stereo-vision. In this special case, we could assume a cube in 3D and search for the regarding vertical and horizontal lines as well, see also figure 2. Together this means that the vision based 3D mapping process is initialized with the 2D information retrieved from laser data. Another example is a poster on a plain wall, e.g. in a hallway. First we find the rectangle describing the poster and measure the pose of the corners in global coordinates, then we relate those coordinates to lines in the 2D-description. If there are matches they are most likely due to the wall measured with the laser range finder. Thus we can correct the pose of the poster according to the laser measurements. In other words, we would certainly not observe the poster without vision, but since depth information obtained using stereo-vision is not as precise as data acquired using the laser range finder, we use the latter to increase accuracy of the 3D-landmarks.

IV. Experimental Results

In this section, we empirically evaluate two aspects of RG mapping: the compactness and accuracy of the resulting maps. Therefore we mapped our recent department building at Or-

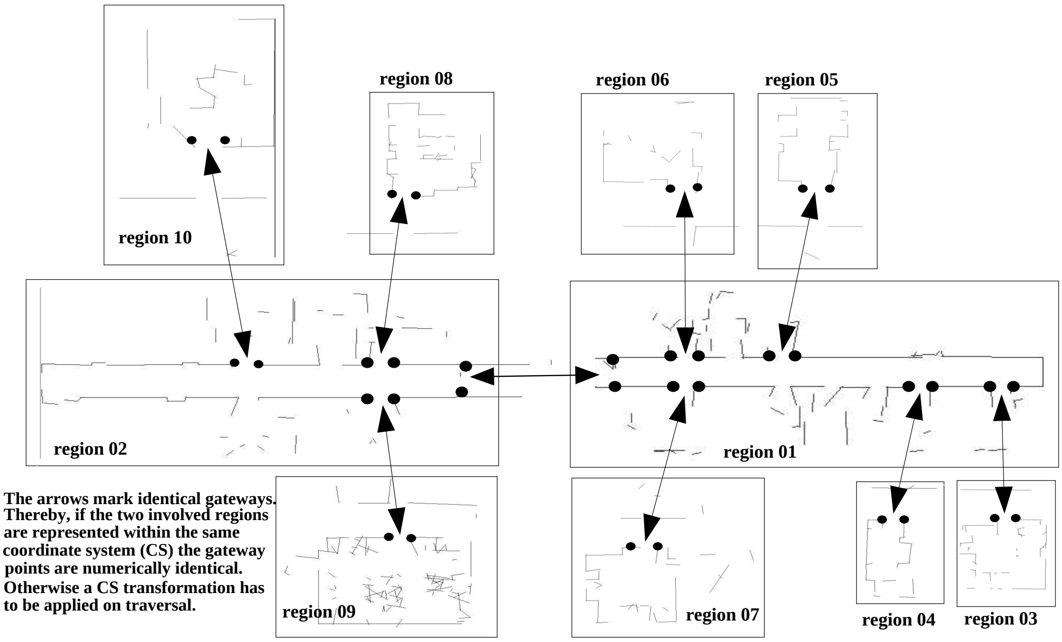

Fig. 4. RG map of our department floor at TUM IX (Orleanstreet, Munich). Raw data: 761 laser scans, ca. 65000 points.

leanstr./Munich which covers an area of about 42x12 meters. The raw data comprises 761 laser scans with approximately 65000 points (see figure 4). A probabilistic occupancy grid map of the same size and with a resolution of 20 centimeters involves about 12600 grid cells. In comparision the RG map we built from the same data can be described with about 600 line segments. Additionally the lines are associated with regions, which results in smaller search space for generating object hypotheses.

Describing the environment with 2D-line segments only leads to data abstraction where in turn essential information might get lost. The question at hand is whether or not the data contained in RG maps is still sufficient for robust localization. Schröter et al. [8] show that RG maps allow robots to localize themselves very acurately. Some of the localization exptertiments can also be found at: http://www9.in.tum.de/people/schroetd/...
...Research/ExploreMovies/movies.html

V. Conclusions

In this paper we have presented ***R***egion and ***G***ateway (RG) mapping, a novel approach to laser-based 2D line mapping of indoor environments. We have shown in experiments on autonomous robots that RG mapping is capable of acquiring very compact, accurate, and region-structured 2D line maps. In our overall research agenda RG maps are an important milestone in our development of a vision-based 3D mapping system that computes maps with 3D object hypotheses. Besides the development of a vision-based 3D object hypotheses generation system we intend to develop better exploration strategies and deal with dynamic objects such as doors.

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