2D Semantic Mapping on Occupancy Grids

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Abstract

In recent years, techniques for building metric maps of indoor environments have been intensely studied, and they perform very well in numerous applications. Simultaneous Localization and Mapping (SLAM) methods produce globally consistent, metric maps of the explored environment. Although such maps describe how the environment looks like, there exist no abstracted semantic concepts that explain the environment on a higher level or in a more natural way (as we humans do), such as, what kind of structure and connectivity the environment possesses. In this paper, we propose a new probabilistic method to analyze the underlying semantic world model based on an occupancy grid map, which is generated by a standard SLAM process. Our approach simulates a Markov Chain that produces samples from the distribution of probable semantic world models given an input map. Experiments show that our approach is effective and correctly captures the uncertainty.

1 Introduction and related work

In recent years, techniques for building metric maps of indoor environments have been intensely studied, and they perform very well in many applications. Simultaneous Localization and Mapping (SLAM) methods produce a globally consistent, metric map of the explored environment. Although such maps describe how the environment looks like, there exist no abstracted semantic concepts that explain the environment on a higher level or in a more natural way (as we humans do), such as, what kind of structure and connectivity the environment possesses. Despite the accuracy of such metric maps, they are still just a huge unsorted matrix containing certain values like occupancy, intensity, etc.. Typical semantic concepts, such as rooms and corridors, or spatial relations like adjacency, connectivity via doors, or properties like rectangularity that – if known to be relevant to the given environment – could help to build the maps in the first place.

Although semantic robot mapping has not been as intensively studied as metric or topological mapping, some notable contributions have already been made. As an early predecessor of many semantic mapping approaches one might consider [11], which combined the grid-based and topological mapping to gain both of accuracy/consistency (metric) and efficiency (topological), the latter effectively by means of abstraction. Wolf and Sukhatme [14] proposed to use hidden Markov models and support vector machines to tackle the problem of terrain mapping and activity-based mapping. [10], [2] and [3] used semantic labels to annotate the places and regions explored by a mobile robot. Douillard et. al. proposed to use conditional random fields to build object-type maps of outdoor environments. Other examples of assigning semantic labels to perceived objects in the explored environments are presented in [7] and [13]. In addition, methods, which semantically annotate the structure of the environments, like traversable terrain in outdoor environments or walls, ceilings and doors in indoor environments, have also been proposed. Some remarkable examples are [8], [12], [6] and [9].

2 Problem description

Different from those methods mentioned above, we aim to construct a probabilistic generative model of the world around the robot, that is essentially based on abstract semantic concepts but at the same time allows to predict the continuous percepts that the robot obtains via its noisy sensors. This abstract model has a form similar to a scene graph, a structure which is widely used in computer graphics. The graph (see Figure 1d) in our case consists of rooms and doorways connecting the rooms and can be visualized as a classical floor plan (see Figure 1b). As a by-product, the connectivity information is represented as a topological map (see Figure 1c) which is of great help for navigation purpose.

The scene graph, i.e. the semantically annotated world state, is represented as a vector of parameters $W$ observed through the occupancy map $M$. In Bayesian framework we can use a maximum posterior approach to infer the most probable state $W^* \in \Omega$ from the space of possible worlds $\Omega$ given the map $M$.

$$W^* = \arg\max_{w \in \Omega} p(W|M),$$

where

$$p(W|M) \propto p(M|W)p(W).$$

Here $p(W|M)$ is the posterior distribution of $W$ given a map $M$, and $p(W)$ is the prior specifying, which worlds $W$ are possible at all. $p(M|W)$ is the likelihood function
describing how probable the observed map $M$ is, given the different possible worlds represented by a parameter vector $W$. The actual semantic model is represented in the structure of the parameter vector $W$, while semantically relevant constraints go into the prior $p(W)$.

3 A generative model for occupancy grids

The prior $p(W)$ in (2) expresses a set of assumptions concerning the structured world based on context knowledge as follows:

1) a room has four walls and possesses a rectangular shape.
2) a room has at least one door, and a door is placed on a wall.
3) each cell in the map should only belong to one room.
4) walls of an indoor environment have two main orientations (see Figure 1b).

The prior $p(W)$ penalizes worlds that are not fully compliant with the above assumptions:

$$p(W) = \alpha_1 \times \alpha_2 \times \alpha_3 \times \alpha_4,$$

where $\alpha_1, \alpha_2, \alpha_3$ and $\alpha_4$ are the corresponding penalization terms for the point 1), 2), 3) and 4) of the prior information respectively.

Furthermore, for our generative model, we need to specify the likelihood function $p(M|W)$. Since $M$ is represented by an occupancy grid with statistically independent grid cells $c \in M$, we only need to come up with a model $p(c|W)$ for all cells at their locations $(x, y)$ in the map $M$:

$$p(M|W) = \prod_{c(x, y) \in M} p(c(x, y)|W).$$

For our model $p(c(x, y)|W)$, we first discretize the cell state $M(x, y)$ by classifying the intensity values into three classes $C_M(x, y)$ according to:

$$C_M(x, y) = \begin{cases} 2, & 0 \leq M(x, y) \leq h_o, \\ 1, & h_o < M(x, y) \leq h_u, \\ 0, & h_u < M(x, y), \end{cases}$$

where $h_o$ and $h_u$ are the intensity thresholds for occupied, unexplored and free cells. Based on our world model $W$ we can also predict expected cell states $C_W(x, y)$ accordingly:

$$C_W(x, y) = \begin{cases} 2, & (x, y) \in S_w, \\ 1, & (x, y) \in S_u, \\ 0, & (x, y) \in S_f, \end{cases}$$

where $S_w, S_u$ and $S_f$ are the set of all the wall cells, unknown cells and free space cells in the world $W$ respectively. $p(c(x, y)|W)$ can then be represented in the form of a lookup-table.

In principle the likelihood $p(c(x, y)|W)$ plays the role of a sensor model. In our case it captures the quality of the original mapping algorithm producing the grid map (including the sensor models for the sensors used during the SLAM process), and could be learned from labeled training data.

4 Searching the solution space

For solving (1) we need to efficiently search the large and complexity structured solution space $\Omega$. Here we adopt the approach of [15], who propose a data driven Markov chain Monte Carlo (MCMC) technique for this purpose. The basic idea is to construct a Markov Chain that generates samples $W_i$ from the solution space $\Omega$ according to the distribution $p(W|M)$ after some initial burn-in time. One popular approach to construct such a Markov chain is the Metropolis-Hastings (MH) algorithm [1]. The Markov

**Figure 1:** a) A simplified occupancy grid map: Unexplored area is drawn in blue, free space is drawn in white. Occupied area is drawn in black. b) A possible floor plan represented as a scene graph ($W$): The world is divided into four rooms and the corresponding unexplored area. Connectivity is given by the color of walls: the color cyan indicates connected, which means there is a door (cyan dotted) between two rooms; the color orange means adjacent, which means that two rooms are neighbor and do not connect themselves through a door; the color black stands for a boundary wall. The detected main orientations of walls are illustrated by violet arrows. c) The connectivity information represented as a topological map of world $W$: Green circles indicate room centers, and red lines connect the room centers and their corresponding doors. d) The semantic description of the world in form of the scene graph: Directed links connect nodes. The dashed lines indicate connectivity which is represented as a topological map in c). Like room 4, each room has three child nodes: walls, free space, and doors. Note that the lowest level of node in the tree structure is the grid cell that either belongs to a wall, free space or a door.
chain is constructed by sequentially executing state transitions (in our case from a given world state \( W \) to another state \( W' \)) according to a transition distribution \( \Phi(W'|W) \) of the sub-kernels. In order for the chain to converge to a given distribution, it has to be reversible and ergodic [1]. The MH algorithm achieves this by generating new samples in three steps. First a transition is proposed according to \( \Phi(W'|W) \), subsequently a new sample \( W'' \) is generated by a proposal distribution \( Q(W''|W') \), and then it is accepted with the probability \( \lambda \).

\[
\lambda(W,W'') = \min \left( 1, \frac{p(W''|M)Q(W|W'')}{p(W'|M)Q(W'|W)} \right)
\]

The resulting Markov chain can be shown to converge to \( p(W|M) \). However, the selection of the proposal distribution is crucial for the convergence rate. Here, we follow the approach of [15] to propose state transitions for the Markov chain using discriminative methods for the bottom-up detection of relevant environmental features (e.g. walls, doorways) and construct the proposals based on these detection results.

In order to realize the Markov chain in form of the Metropolis-Hastings algorithm, we arrange the kernels that alter the structure of the world as reversible pairs: ADD or REMOVE one room; SPLIT one room or MERGE two rooms; SHRINK or DILATE one room; ALLOCATE or DELETE one door.

Figure 2 shows an example of the four reversible MCMC kernel pairs. The world \( W \) can transit to \( W', W'', W''' \) and \( W'''' \) by applying the sub-kernel REMOVE, MERGE, SHRINK and DELETE, respectively. By contrast, the world \( W', W'', W''' \) and \( W'''' \) can also transit back to \( W \) using corresponding reverse sub-kernels.

The proposal probability \( Q(W'|W) \) and \( Q(W|W') \) describe how probable the world \( W \) can transit to the world \( W' \) and \( W'' \) can transit to \( W \) respectively. They can be calculated in the following general form:

\[
Q = p_k \times p_e,
\]

where \( p_k \) is the probability of choosing a certain sub-kernel to perform the transition. \( p_e \) is the probability of choosing a certain element of the semantic world to change.

5 Experiments and discussions

Our approach was tested in several online and offline experiments. In online runs, we only utilize the robot position to propose new room candidates, since it is straightforward that there must exist a small free space around the current robot position. Thus, for the online runs, the discriminative method for the sub-kernel ADD is just generating a small rectangular region around the robot position. Then, these generated regions are locally adapted by other sub-kernels so as to better match the map. For offline runs, the information on robot position is not available, thus the discriminative method for proposing room candidates in ADD mainly focuses on finding room-like regions in the input map, and these regions are used as room candidates. Other sub-kernels stay the same as in online runs.

Once the semantic world model is built, the corresponding topological map can be easily computed based on the connectivity information. There are many ways to generate it, and in this paper, we just adopt a simple strategy which connects the room centers with the mid-point of their corresponding doors.

One example of an online run is depicted in 12 steps in Figure 3. In step 2), a room is proposed and added into the world. This room becomes bigger and bigger through many successful DILATE, as shown in step 3). Sub-kernels except ADD and DILATE tend to be rejected during this period, because they do not help to better explain the map. The same process happens again in step 4) to 6) and step 7) to 10). In step 11), a new room is generated through a successful SPLIT, and again, it is changed by DILATE to generate the final result shown in step 12.

Figure 3: One example of an online run shown in 12 steps. Boundary walls (blue), adjacent walls (orange) and doors (cyan) of the world drawn into the classified map. The violet point depicts the robot position.

Figure 4 shows the final result of the online run explained above in some more detail. Here, part a) shows the final input occupancy map \( M \). Part b) shows the classified map \( C_M \) that is defined in (5), with the color black, gray and white indicating occupied, unexplored and free cells, respectively. Part c) visualizes the world state \( W \) representing our structured semantic model. Here the colors...
black, gray, white and cyan show the wall, unknown, free
and door cells respectively. The corresponding topologi-
cal map is also depicted. In part d), boundary walls (blue),
adjacent walls (orange) and doors (cyan) of the world W
are directly plotted onto the classified map, so as to give
a more intuitive comparison. Another example of an on-
line run is illustrated in Figure 6. Figure 7 demonstrates a
result obtained offline for a much bigger environment.

Figure 4: Final Result of the online run shown in Fig-
ure 3. a) An input map \( M \) containing no furniture. b) The
classified map \( C_M \) with three intensity values (black=wall,
grey=unexplored, white=free). c) The analyzed world \( W \)
(black=wall, gray=unknown, white=free, cyan=door) and the
corresponding topological map (green circles=room centers). d) A
direct comparison between the analyzed world and the input
map: boundary walls (blue), adjacent walls (orange) and doors
(cyan) of the world W drawn into the classified map.

In order to quantitatively evaluate our approach, we com-
pute \( K(W, M) \), the cell prediction rate capturing the pre-
dictive power of the semantic world model \( W \) and with
respect to an input map \( M \):

\[
K(W, M) = \sum_{c(x,y) \in M} l(c(x,y)) / t_M,
\]

where \( t_M \) is the number of all grid cells in the map \( M \).
c(\( x, y \)) indicates one grid cell located at the position \( (x, y) \).
\( C_M(x, y) \) and \( C_W(x, y) \) are previously defined in equation
(5) and (6). \( K(W, M) \) of the maps shown in this paper is
summarized in Table 1.

Our approach simulates a MCMC sampling which effect-
ively draws samples from the underlying distribution of the
semantic world model. In Figure 5, we illustrate this
distribution by plotting 10000 samples together, which are
obtained after the initial burn-in time. For illustration pur-
poses, the walls of the semantic world model are drawn as
very thin lines (see one sample in Figure 5a), so that the
variance of the predicted wall postions can be seen as wall
thickness in the overlay image (see Figure 5b). In contrast
to a single sample, whose walls are partially too thin to be
seen, the overlaid walls of 10000 samples almost fill all of the
occupied cells of the input map, i.e. the thickness of the
“real walls”. It is obvious that our approach correctly
captures the uncertainty of the semantic world model. In
comparison with the map of the online run shown in Fig-
ure 4a, the offline map in Figure 7a is much more compli-
cated (mainly due to false positives caused by furniture or
other objects), thus, the uncertainty of the semantic world
model for this offline map is much bigger, as depicted in
Figure 8b.

Table 1: Cell prediction rate \( K(W, M) \).

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<th>Figure 4 d)</th>
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<tr>
<td>Percentage</td>
<td>98.7%</td>
<td>93.8%</td>
<td>93.6%</td>
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Figure 5: a) A single sample of the semantic world model. b) The
distribution of the semantic world model for the map shown
in Figure 4a built by 10000 samples. Note that the walls of each
sample are drawn as very thin lines. The overlaid walls of 10000
samples almost fill the thickness of “real walls”, which makes it
evident that our approach correctly captures the uncertainty of the
semantic world model.

Figure 6: Another example of an online run using an input map
which contains furniture. Color coding is the same as Figure 4.
**Figure 7:** One example of an offline result. a) An occupancy grid map $M$ [5]. b) The classified map $C_M$ with three intensity values (black=wall, grey=unexplored, white=free). c) The analyzed world $W$ (black=boundary wall, orange=adjacent wall, gray=unknown, white=free, cyan=door). d) Boundary walls (blue), adjacent walls (orange) and doors (cyan) of the world $W$ drawn into the map. e) Generate the topological map using the connectivity information. f) The resulting topological map (green circles=room centers).

**Figure 8:** a) A single sample of the semantic world model. b) The distribution of the semantic world model for the map shown in Figure 7 a) built by 10000 samples. For illustration purpose, adjacent walls are not shown. Note that the walls of each sample are drawn as very thin lines.
In this paper, we make use of some basic assumptions concerning the environment to infer its semantic structure. The assumptions describe a common environment type being mainly rectangular. However, our approach is in general not restricted to the specific assumptions used here, and it can be extended for other forms by incorporating new room types and corresponding discriminative methods. Currently, our implementation is single-threaded. On an Intel Core i7 CPU with 2.0 GHz, the online mode can be finished within the runtime of the underlying SLAM process [4] which provides the input map for our algorithm. Of course, the computing speed largely depends on the size of the map that is to be analyzed (Figure 7, 1237×672, ∼1 min).

6 Conclusions and future work

In this paper, we propose a new probabilistic method to extract the underlying semantic model of a given indoor environment based on an occupancy grid map that is generated by a standard SLAM process. Our approach implements a data driven Markov Chain Monte Carlo sampling procedure to draw samples from the distribution of possible semantic world models given this input map. Based on a few reasonable assumptions concerning the nature of indoor environments, we represent the domain in an abstracted, semantic and top-down manner, i.e. containing several rooms connected by doorways. Meanwhile, by using several discriminative environment feature detectors to propose Markov chain transisions, the method also incorporates a bottom-up path.

The method allows us to effectively sample from the probability distribution of possible interpretations of the continuous and noisy sensor observations. This is used here as a basis for finding the best explanation of the grid map in the maximum likelihood sense, and provides the robot with a structural understanding of its environment that can be used for a wide range of higher-level reasoning or communication purposes. At the current stage, our approach is limited to 2D cases, in which we build a classical floor plan from occupancy grids including semantic concepts. In the future, we will focus on extending our approach to 3D scenarios and enriching our world model with other semantic concepts.

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