Extraction of IndoorGML Model from an Occupancy Grid Map Constructed Using 2D LiDAR

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Abstract: Topological semantic indoor spatial data is deemed important for efficient navigation of mobile robots and humans alike. In an effort to standardize and facilitate interoperability of indoor spatial data, the Open Geospatial Consortium has adopted the IndoorGML spatial data model. There has been a research gap identified in the use of such high-level, semantically rich spatial data (e.g. IndoorGML) in a Simultaneous Localization and Mapping framework. This paper presents an entry-point study towards addressing this research gap by presenting a method based on mathematical morphology as a means of extracting topological and semantic information from occupancy grid maps. The extracted semantic & topological information is translated into an IndoorGML compliant semantic Node-Relation-Graph and validated against the OGC IndoorGML schema.

1 Introduction

Along with the advent of SLAM (Simultaneous Localization and Mapping) algorithms, autonomous service robots have been gaining popularity which is justified by the availability of numerous consumer assistive robots such as the "Roomba" autonomous vacuum cleaner and the Care-O-bot from Fraunhofer IPA. Such service robots can be used in a range of scenarios ranging from home and personal assistive systems to industrial applications. In order to accomplish their task, especially those exclusively operating in an indoor environment, require the use of some sort of spatial representation of the environment.

Indoor map representation and navigation problems have been long addressed by the robotics community in light of autonomous navigation of robots. Different map representation models have been proposed, such as: feature based maps, semantic maps and topological maps. It is often the case that algorithms involved in the generation of maps are geared towards producing point clouds as end products. A significant challenge with point clouds is that, they do not provide high level understanding of the environment. High level information in a form of semantic or topology information is deemed valuable especially when it comes to applications in Building Information Modeling (BIM) and Location Based Services (LBS).

High-level map representation in SLAM, especially in the case of service robotics facilitates semantic understanding and human-robot interaction. Integration with the Open Geospatial Consortium (OGC) indoor spatial data model standard – IndoorGML could be realized as an implementation of semantically and topologically rich map information in a SLAM framework. The integration of semantic and topologic information for example in the graph based SLAM frame-

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work introduces new challenges and opportunities in implementing optimization algorithms that make use of metric and non-metric information.
Indoor LBS require spatial models that support attribution of semantic properties, contain accessibility information, store spatial relationships and serve for the function of multi-modal navigation. The complex nature of indoor scenarios added to the diversity of users and diverse navigation modalities asks for a flexible and efficient spatial data model that is useful for agents navigating in an indoor environment.

2 Problem statement

The robotics community has been highly invested on the use of point clouds or Truncated Signed Distance Functions (TSDF) to model 3D geometry. The disadvantage in using such representations is that they have large memory footprints and they do not inherently provide high level understanding of the geometric representation (CADENA et al. 2016). The most important aspect of high-level map representations relevant to this study is the capability of such representations to facilitate interaction between robotic maps, Geographic Information Systems (GIS) and Building Information Modeling (BIM) standards. IndoorGML is a standard with a potential to address this issue of interoperability. CADENA et al. (2016), after providing an elaborate discussion on state of the art in high-level map representation, formulates that ". . . no SLAM techniques can currently build higher-level representations, beyond point clouds, mesh models, surface models and TSDFs." Based on this premises this paper presents an entry point study, which later on expands to the use of IndoorGML models in a SLAM framework.
Occupancy grid maps are primarily intended to be used for robot navigation related tasks, whereas with the introduction of the IndoorGML standard, the usability of occupancy grid maps could be further extended as sources of up to date indoor spatial information that is usable to applications in indoor GIS and pedestrian navigation.
The IndoorGML standard highlights the importance of indoor sub-spacing. Sub-spacing is important to represent the geometric properties of an indoor space. An example for a need for sub-spacing is a situation where an indoor space has a large and complicated corridor structure where the representation of such space as a single unit might hide meaningful geometry which could be useful for navigation tasks.

3 Related work

3.1 IndoorGML

SRIVASTAVA et al. (2018) developed a methodology to convert CAD drawings of indoor building data into IndoorGML. They extended the IndoorGML core module to handle semantic information. Their approach relies on the availability of CAD DXF floor plan. Similarly, PANG et al. (2018) proposed a method to extract a building's indoor space information based on simple indoor space boundary calculation on an already existing BIM and GIS models. On the other hand, DÍAZ-VILARIÑO et al. (2017) investigated a method to extract IndoorGML model from point cloud data acquired from a SLAM based 3D mapping system (laser scanner); their approach made use of the sensor trajectory computed from the mapping system along with region growing and adjacency analysis to extract semantic information and reconstruct the scene.

DIAKITÉ et al. (2017) discuss a set of recommendations for the OGC IndoorGML standard with the intent of improving the standard in future versions. They primarily investigated problems related to the space subdivision concept in IndoorGML. It is pointed out that the current version (1.3) of the standard fails to address the context of furnished 3D indoor environments. The authors propose a multi-criteria approach (Geometry-driven, Topology-semantic-driven and navigation driven criteria) towards automatic subdivision of space cells.

3.2 Extraction of Topology from Occupancy Grid Maps

JOO et al. (2010) propose a method for automatic generation of topological maps from occupancy grid maps using virtual door detection. Their method is implemented in two phases where virtual doors are detected from the occupancy grid using adaptive curvature estimation of corner features in the first phase and the topological structure extracted from the first phase is optimized by the use of a genetic algorithm in the second phase. Despite the homogenous nature of the environment where their experiments were carried out, the authors claim that their approach has a high degree of accuracy.

Image processing techniques could be used to extract high-level information from occupancy grid maps (FERNÁNDEZ-MADRIGAL & BLANCO CLARACO 2013; ELFES 1989). Alternatively, a learning based approach using artificial neural networks and Bayesian integration has been successfully implemented by THRUN & BÜCKEN (1996) for the same purpose. They used an artificial neural network to interpret sonar sensor reading into an occupancy grid map whereas the topological map is generated by splitting the metric map into sub-regions by identifying critical points on a Voronoi diagram that are closest to an occupied grid cell within a given neighborhood and connecting these points to the corresponding occupied grid cell by critical lines which represent doorways. Even though this approach perfectly fulfills its purpose when it comes to navigation, it lacks the semantic labeling aspect where indoor spaces are labeled as transition spaces (corridors and doors) and rooms.

POTUGA & ROCHA (2012) implemented an image processing based approach similar to the methodology adopted in our study. Their work in general deals with obtaining a global topological abstraction from a preexisting occupancy grid map. The topological structure is basically extracted from the skeletonization of free space which results in a Voronoi diagram. Corner points on the Voronoi diagram are considered as nodes and the lines between such nodes constituted the edges of the graph. One major drawback of this approach when it comes to the Node Relation Graph concept of IndoorGML is that the graph constructed this way does not portray the actual semantic & topological relationship of the primal space. For instance, there is no means of telling which nodes are rooms, corridors or doors.

To summarize, research in the extraction of topological information from occupancy grid maps could be categorized in to two as machine learning based and image processing based approaches. Our approach belongs to the later and incorporates both topological and semantic indoor information as per the IndoorGML standard.

4 Method

4.1 Simulation & Data Acquisition

Our study presents a set of methods to extract 2D IndoorGML model from an occupancy grid map generated by a simulated indoor robot fitted with a 2D LiDAR sensor. In order to generate the occupancy map, a particle filter based open source SLAM algorithm known as “gmapping” (GRISETTI et al. 2007) is used as a black box. The simulation is carried out in the ROS-GAZEBO robot simulation environment where two scenarios, a simple hypothetical 3D floor plan and the popular “Willow garage” floor plan were used. The data was acquired by driving a robot fitted with a 2D LiDAR in the simulation environment.

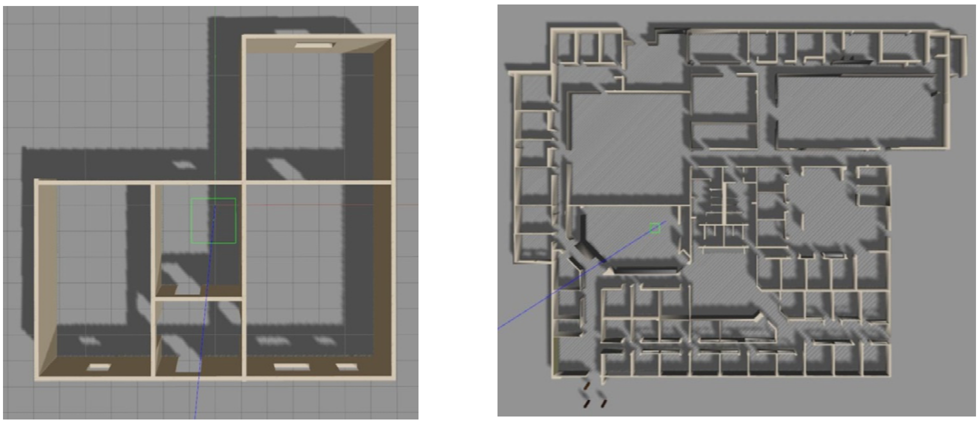


Fig. 1: A simple hypothetical 3D floor plan (left) and the Willow garage dataset (right)

4.2 IndoorGML

The OGC IndoorGML standard is developed as an application schema of the Geography Markup Language (GML) with an intension to facilitate the representation and interoperability of indoor spatial data for the purpose of indoor navigation. One of the intended application area for IndoorGML is in the localization of features in indoor space. It is meant to address requirements for representing spatial components and constraints defined by architectural components such as rooms, corridors and doors and the respective relationships among these components. The standard defines indoor constraints based on the notions of cellular space, semantic representation, geometric representation, topological representation and multi-layered representation (LEE & LI 2012).

Since the main purpose of the standard is to provide a framework for indoor spatial data oriented towards navigation, the semantics aspect of indoor space is also dealt from the point of view of indoor navigation where indoor cells are classified into navigable and non-navigable cells (LEE & LI 2012). Although IndoorGML supports both geometric and topological information, we focus on the network representation of cellular space, which in our case is to be extracted from occupancy grid maps. By network representation, it implies topological relationship which also might contain some level of semantic information. IndoorGML proposes the use of a Node-Relation Graph (NRG) to represent topological relationships such as adjacency and connectivity.

In order to represent a cellular (geometric) indoor space in to a graph structure, the IndoorGML standard makes use of the theory of Poincaré duality. In Poincaré duality applied to indoor space, a room is to be represented as a point and the adjacency between rooms (shared 3D wall or 2D line) is to be represented by an arch connecting the two spaces. The standard identifies two sorts of adjacency properties, connectivity and accessibility.
The notion of Node-Relation Graph lends itself to the idea of graph data structure commonly known in mathematics and computer science. A graph generally represents relationships between pairs of objects commonly called nodes or vertices. This relationship is represented by a set of pairwise connections between nodes referred to as edges. A formal definition of a graph is given by MARCHAND-MAILLET & SHARAIHA (2000) as: *A graph $G = (V, E)$ is a set of vertices V with their inter-relationships given by the set of arcs E. If an orientation is associated with any arc, the graph is said to be directed otherwise G is an undirected graph.* In this paper, when we only assume undirected graphs where the set of all possible relations between nodes is given by:

$$\boldsymbol{H} = \bigcup_{i}^{N} C(v_i, 2) \ ; \ G \subset \boldsymbol{H} \tag{1}$$

Where V represents the set of all vertices V_i and all possible edges are represented as pairwise combination of all vertices (nodes). An instance of **H** which represents a particular configuration space of an indoor environment - G is a set of nodes and edges in dual space.

4.3 Image Operations on Occupancy Grid Maps

The concept of occupancy grid maps as a probabilistic tessellated space representation of spatial information was first introduced by ELFES (1989). A formal definition of occupancy grid map is given as: "*An occupancy field $O(x)$ is a discrete-state stochastic process defined over a set of continuous spatial coordinates $x = (x_1, x_2 \ldots x_n)$ while the occupancy grid is a lattice process, defined over a discrete spatial lattice*". Each occupancy grid cell "c" is associated with a binary random variable $s(c)$ with a Bernoulli distribution (FERNÁNDEZ-MADRIGAL & BLANCO CLARACO 2013; ELFES 1989). One advantage of occupancy grid maps is that they seamlessly fit into Bayesian particle filter based recursive estimation algorithms; on the other hand their huge storage requirement makes them infeasible options for mapping large scale environments (FERNÁNDEZ-MADRIGAL and BLANCO CLARACO 2013).
For the sake of simplicity, we describe the occupancy mapping approach in the case of mapping with a known pose (THRUN et al. 2005; FERNÁNDEZ-MADRIGAL & BLANCO CLARACO 2013). The posterior to be estimated under this assumption is the map given by the conditional probability $p(m|z_{1:t}, x_{1:t})$ for each pixel grid cell m_i and all sets of measurements and poses up to time t. The posterior becomes tractable if the individual distributions on m_i are estimated rather than on the whole joint probability. Assuming that the individual grid cells are independent from each other, the posterior could be simplified as a product of its marginal given by:

$$p(m|z_{1:t}, x_{1:t}) = p(\{m_i\}_i^N | z_{1:t} x_{1:t}) \approx \prod_{i}^{N} p(m_i | z_{1:t}, x_{1:t}) \tag{2}$$

After successive application of Bayes rule, the conditional independence assumptions given by $z_t \perp z_{1:t-1} | \, x_t, m_i$ and $m_i \perp x_{1:t}$ enable the formulation of the log odds of the posterior $p(m_i | z_{1:t}, x_{1:t})$ as:

$$l_t(m_i) = \tau_t(m_i) - \, l_o(m_i) + l_{t-1}(m_i) \tag{3}$$

Where:

$l_t(m_i) = \ln \frac{p(m_i | z_{1:t}, x_{1:t})}{p(\neg m_i | z_{1:t}, x_{1:t})}$, the log odd of the posterior to be estimated;

$\tau_t(m_i) = \ \ln \frac{p(m_i | z_t, x_t)}{p(\neg m_i | z_t, x_t)}$, the inverse sensor model of a 2D LiDAR for a given grid cell;

$l_0(m_i) = \ \ln \frac{p(m_i)}{p(\neg m_i)}$, represents a-priori information about the map occupancy;

$l_{t-1}(m_i) = \ln \frac{p(m_i | z_{1:t-1}, x_{1:t-1})}{p(\neg m_i | z_{1:t-1}, x_{1:t-1})}$, the previous occupancy state of the grid cell;

4.3.1 Mathematical Morphology

Occupancy grid maps can be transformed into binary images that represent occupied space as black pixels and free space as white pixels by thresholding. This enables the use of morphological operations to manipulate the geometric content based on the contents of neighboring pixels defined by a structuring element. In this sub-section we understand occupancy grid maps as simple binary images with values 1 as foreground pixels and 0 as background pixels. Onwards, we make use of formal definitions of morphological filters and operations given by BURGER & BURGE (2009).

Dilation: $I \oplus H \ \equiv \{(p+q) | \forall \, p \ \in I, q \in H\}$

Erosion: $I \ominus H \ \equiv \{p \in Z^2 | (p+q) \in I, \forall \, q \in H\}$

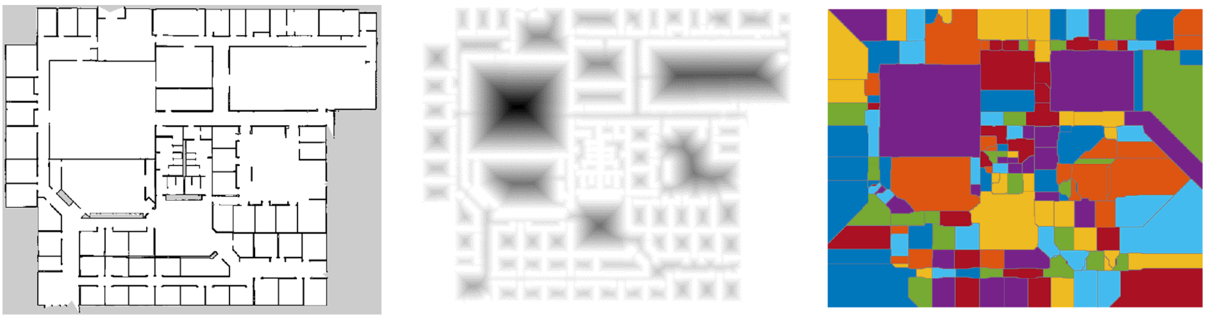
Opening: $I \circ H = (I \ \ominus H) \oplus H$

Closing: $I \bullet H = (I \ \oplus H) \ominus H$

Skeletonization is the process of converting foreground pixels in to strings of single pixels which capture the geometric essence of the foreground pixel components in the image. Skeletonizing an occupancy grid map leads to the representation of free space by a string of pixels which capture the geometric nature of the free space. In this regard, we have made use of Blum's Medial Axis Transform (MAT) (BLUM 1967) to construct skeletons of from occupancy grid maps. Such representation of free space is often referred to as generalized Voronoi graph (diagram).
One drawback of using morphological filters is the specification of the structure and dimension of the structuring element which needs to change as per the texture of the image to be used. The use of a suitable parameter depends on a prior knowledge of the environment such as width of doorways and corridors. In addition, certain morphological operators with a square structuring element work best on Manhattan like environments and perform weakly on other environments.

4.3.2 Morphological Segmentation (Watershed Transform)

The watershed transform borrows the notion of a watershed and catchment basin from physical geography. In geography, a watershed is an area of land that marks the boundary of a catchment basin. A catchment basin on the other hand represents the area of land where water drains off into a common pour point. Generation of a watershed or catchment is commonly performed from a digital elevation model in geography.
In image processing, the watershed transform is commonly used along with the distance transform. The result of a watershed transform in MATLAB is a label matrix which represents individual catchment basins where the watershed ridge pixels have a value of zero (GONZALEZ et al. 2009). One major drawback of watershed based segmentation is that without the use of interactively provided markers, the result could be over-segmented due to noise and other local irregularities.



(a) (b) (c)

Fig. 2: Watershed transform (c) on an occupancy grid map (a) and the corresponding distance transform (b).

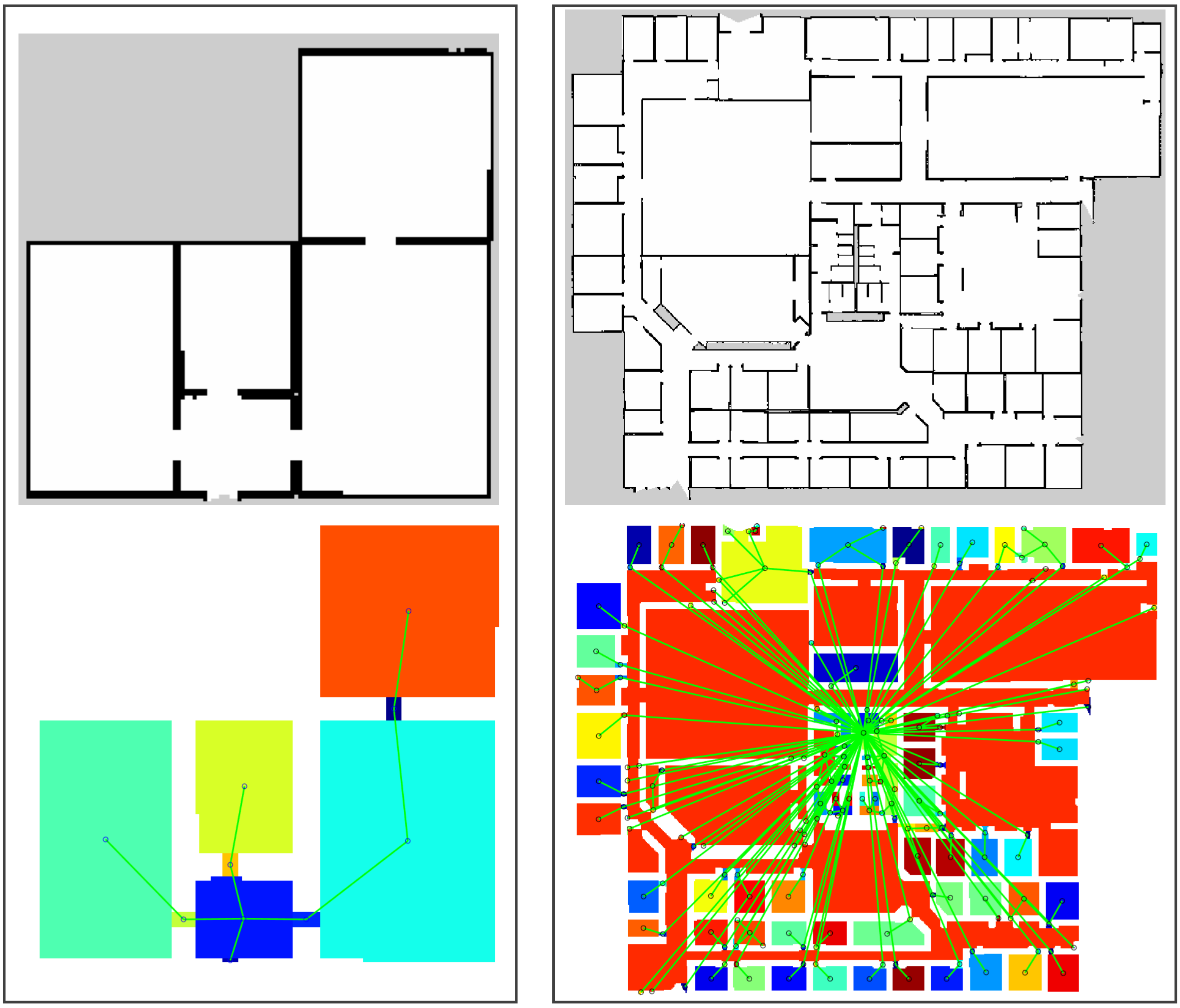
4.3.3 Region Adjacency Graph (RAG)

Once the occupancy grid map is converted in to a symbolic image (segmented & labeled), the next step would be the extraction of the topological relationships among the labeled image components. The result of such operation is a region adjacency graph that stores spatial adjacency information. This final graph structure corresponds to IndoorGML's NRG and is later translated in to an IndoorGML file and was validated against the OGC IndoorGML schema online.
In order to extract a RAG from a symbolic image, horizontal and vertical adjacencies (4-adjacency) between pixels with different labels are detected and these are added as new edges to the adjacency graph being constructed. In this study, we have made use of the algorithm proposed by SHAPIRO (1996) for the extraction of region adjacency from a labeled occupancy grid map.

5 Results

5.1 Experiment I

In the first experiment, we investigated the results of binary connected component labeling after elementary morphological operations were performed on an occupancy grid map. The method implemented for this experiment is presented in Tab. 1. In steps 1 and 2 the input occupancy map is binarized and the walls are further articulated by a dilation operation. Steps 3 to 6 deal with the extraction of doors. Finally, the region adjacency is computed by the method mentioned in section 4.3.3. As shown in Fig. , the algorithm performs well in the hypothetical (simple) dataset. Whereas in Fig. (b), it is shown that the applied method fails to cope with the scale and complexity of the Willow garage dataset. From the results, one could understand that the fundamental factor that contributes to the success or failure in this approach is the homogeneity and complexity of the environment.



(a) (b)

Fig. 3: Occupancy grid maps and their corresponding NRG extracted using connected component labeling. (a) On a hypothetical environment and (b) On the Willow garage dataset.

Tab. 1: Method for the extraction of NRG based on connected component labeling.

Method: NRG from Connected Component Labeling
1. Binarize occupancy grid map $I_{bin} = binarize(I_{occ}, 0.85)$ 2. Morphological erosion $I_{erd} = I_{bin} \ominus SE$ 3. Morphological Opening $I_{opn} = I_{erd} \circ SE$ 4. Connected component labeling $I_{label} = label(I_{opn})$ 5. Binary XOR to detect doors & label doors $I_{door} = label(I_{opn}\, XOR\, I_{erd})$ 6. Reintroduce doors in the symbolic image (join the two labels) $I_{label} = I_{door} \cup I_{label}$ 7. Generate region adjacency graph $G_{RAG} = regionAdjacency(I_{label})$ 8. Write G_{RAG} to IndoorGML as NRG

Fig. 6(b) (bottom) shows the region adjacency graph generated from the labeled symbolic image of the willow garage dataset. In such a graph the nodes actually represent the centroid of the corresponding labeled component. It is for this reason that all the edges appear to converge to the center of the largest component, which is the corridor in this case. Due to this phenomenon it is not possible to represent the actual topological & geometric structure of the environment using the method described in Tab. 1. Furthermore the door detection (step 5) which uses XOR operator on I_{opn} and I_{erd} results in incorrect regions due to the effect of the morphological thickening that also affects other regions of the image.

5.2 Experiment II

In the second experiment, we addressed the limitations discussed in experiment I. Furthermore, we made use of the watershed segmentation method to further subdivide the corridor so that the actual geometric structure of the environment could be preserved. For the detection of doors, we adopted a new method that makes use of the medial axis transform. The skeletonization of pixels representing empty space (white) results in what is known as the generalized Voronoi diagram. A generalized Voronoi diagram is the generalization of the ordinary Voronoi diagram of points. In this particular case the generalization would be in the use of the medial axes as seeds (instead of points). On the other hand, the complement of I_{opn} was also skeletonized and the intersection (step 3 on Tab. 2) of these and the Voronoi pixels were considered to be transition spaces (doorways).

Tab. 2: Method for door detection using skeletonization

Method: Door Detection using Medial Axis Transform (MAT)
1. Skeletonization of boundaries using MAT $I_{skel} = skeleton(inverse(I_{opn}))$ 2. Generalized Voronoi graph $I_{vor} = skeleton(I_{opn})$ 3. Intersection of I_{vor} and I_{skel} $I_{door} = label(I_{skel}\ AND\ I_{vor})$

The detection of doors plays a major role in the semantic labeling of the whole grid map. After all the candidate doors were detected as per the method shown in Table 2, the NRG was initialized as a node only graph with the centroid of the door pixels. The connectivity information was added incrementally by introducing the labeled image from the watershed segmentation. In order to identify rooms and corridors, a rule was formulated where non-door nodes with a degree of two or more are labeled as a transition (corridor) spaces as shown in Table 3, step 6.

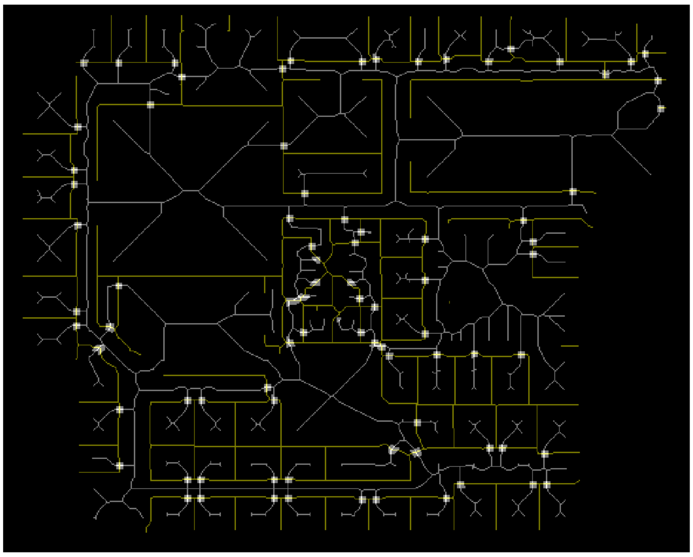


Fig. 4: Detection of door pixels using intersection of complementary skeleton pixels I_{skel} (yellow) and I_{vor} (gray)

Once the RAG was generated from the union of the labeled image which is a result of the watershed segmentation and the labeled door image, further refinement of the graph was carried out by introducing topological constraints based on a-prior knowledge. Cyclic sub-graphs which are caused by the over-segmentation during watershed transformation were removed by applying these constraints in a post processing stage. Cyclic corridor-corridor-corridor sub-graphs were modified in a similar fashion as described inTab. 4. Reflexive node relationships were also used as a constraint to avoid door-door and room-room adjacencies. Edges representing such connections were simply deleted from the NRG. We have also imposed a constraint to remove “dangling” (degree = 1) corridor nodes as this conflicts with our definition of a corridor, which is a node in the NRG with a degree of at least 2.

Tab. 3: Procedure for generating IndoorGML NRG from RAG obtained from watershed segmentation

Method: IndoorGML NRG Generation from RAG

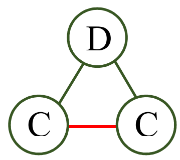
1. Initialize G with door nodes
   $G_{NRG}(nodes) = unique\ (I_{door})$
   $G_{NRG}(edges) = \emptyset$
2. Append space nodes from watershed label to G
   $G_{NRG} = addNode(unique(I_{label}))$
3. Reintroduce doors in the symbolic image (join the two symbolic images)
   $I_{label} = I_{door} \cup I_{label}$
4. Generate region adjacency graph
   $G_{RAG} = regionAdjacency(I_{label})$
5. Add edges to graph
   $G_{NRG}(edges) = G_{RAG}(edges)$
6. Find corridor nodes using degree of node
   $trans = degree(G_{NRG}(nodes)) \geq 2$
   $\neg doors = G_{NRG}.type \neq 'door'$
   $corridors = trans \cap \neg doors$
7. Assign edge weights based on connectivity
   $edge(n_{door}, n_{door}).weight = -1$
   $edge(n_{room}, n_{room}).weight = -1$
   $edge(n_{corridor}, n_{corridor}).weight = 0$

A visual comparison of the NRG with and without the refinement is presented in Fig. 8. The refinement of the RAG extracted from watershed segmentation by modifying cyclic sub-graphs as per the method described inTab. 4 resulted in a simplification of the graph structure. Fig. 8(b) shows the final and simplified semantic-topological map of the Willow garage dataset where the ID of each graph node corresponds to the label of the respective region in the binary occupancy grid map.

Tab. 4: Procedure for refining the NRG by modifying cyclic sub-graphs

Method: Modify cyclic corridor-door-corridor sub-graphs

$for\ all\ (n_i.type ==' door')in\ G_{NRG}\ do$
 $n_{nh} = neighbors\ (G_{NRG}, n_i)$
 $e_{nh} = {}_{n_{nh}}C_2$
 $for\ all\ e^i_{nh} in\ G_{NRG}\ do$
  $if(e^i_{nh}.weight == 0)$
   $delete\ e^i_{nh}$
  $endif$
 $endfor$
$endfor$



(a)

(b)

Fig. 5: Semantic topological map before (a) and after NRG refinement (b). In (b) spurious triangular cyclic sub-graphs are removed.

6 Discussion

In order to acquire an overall accuracy assessment, the final result on Fig. 8(b) was visually compared against a manually labeled image, which served as a ground truth. On the ground truth, there were a total of 84 doors and 65 rooms identified. A label was considered as accurate or not based on a prior definition of doors and rooms. For example, a structuring element of 15 by 15 was used in the process of door detection, which implies (with a pixel size of 0.1) doorways only under 1.5 meters were considered as true doors. And rooms are considered to be nodes with a degree of 1. Based on these assumptions, it was possible to achieve an accuracy of 90.5% for door detection. 62.5% of the errors (missed & wrong labels) are within the toilet area (highlighted in black rectangle on Fig. 8(b)), where the rooms are significantly small that the applied morphological operations resulted in loss of details. Finally, the room labeling accuracy was at 90.76% with 66.67% of the errors still lying within the toilet area. Outside the toilet area, there were only 2 wrong labels of rooms. Two room nodes that are accessible through more than one doorway (node degree > 1) were labeled as corridors and these are not considered as failure cases as they comply with the prior definitions of a rooms and corridors.

7 Summary

In this paper, we presented a semi-automatic method for the extraction of IndoorGML model from occupancy grid maps. Our approach laid out the foundations towards an automatic extraction of graph based semantic indoor data without the need for a learning based approach. The next step in this regard would be manipulation of the mentioned core image processing algorithms such as watershed transform and connected component labeling, in a way that is possible to handle arbitrarily scaled environments without manual adjustment of parameters, particularly of the structuring element in morphological operations.

The core of our approach lies on the detection of doors based on the results of medial axis transformation and refinement of the graph structure computed from region adjacency. The results presented could be considered as initial attempts to extend the functionalities and usability of indoor robot maps for the purpose of extracting meaningful information relevant to BIM and GIS. Next, our investigation continues to investigate the same problem in realistic occupancy grid maps constructed from real indoor environments. We assume working on a real dataset poses additional challenges especially when it comes to the detection of doors.

Further investigation in this line of research would focus on the use of hierarchical graph structures to elegantly handle the subdivision of complex indoor spaces, introduction of multi-layered grid maps with additional information layers (such as curvature from point clouds) and introduction of an IndoorGML model updating procedure based on change detection framework.

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