

Reconstruction and Prediction of the Layout of Indoor Environments from Two-Dimensional Metric Maps

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Abstract

Metric maps, like occupancy grids, are one of the most common ways to represent indoor environments in autonomous mobile robotics. Although they are effective for navigation and localization, metric maps contain little knowledge about the structure of the buildings they represent. In this paper, we propose a method that identifies the structure of indoor environments from 2D metric maps by retrieving their *layout*, namely an abstract geometrical representation that models walls as line segments and rooms as polygons. The method works by finding regularities within a building, abstracting from the possibly noisy information of the metric map, and uses such knowledge to reconstruct the layout of the observed part and to predict a possible layout of the partially observed portion of the building. Thus, differently of other methods from the state of the art, our method can be applied both to fully observed environments and, most significantly, to partially observed ones. Experimental results show that our approach performs effectively and robustly on different types of input metric maps and that the predicted layout is increasingly more accurate when the input metric map is increasingly more complete. The layout returned by our method can be exploited in several tasks, such as semantic mapping, place categorization, path planning, human-robot communication, and task allocation.

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1. Introduction

Understanding the environments in which they operate is an important capability for autonomous mobile robots. Buildings are strongly structured environments that are often organized in regular patterns. The identification of the building structure is useful for several tasks, such as semantic mapping, place categorization, path planning, human-robot communication, and task allocation [1]. For instance, knowledge about the building structure can be useful to efficiently spread the robots to incrementally build a map of an initially unknown environment, in the context of coordinated multirobot exploration [2].

Metric maps, like grid maps [3], which are the usual environment representation employed in autonomous mobile robotics, do not explicitly contain any knowledge about the building structure, but only represent the space occupation for navigation and localization purposes. In addition, metric maps may contain several inaccuracies and missing data, since portions of the environment may not be observed by the robot, as in case of occlusions or during exploration.

The *layout* of a building is a geometrical representation of its walls and rooms that provides a “clean” and stable knowledge about the structure of the building, disregarding information about furniture and regularizing noisy and missing data, which often affect metric maps. Each room is represented either by a polygon (in 2D) or by a box model or a set of planes (in 3D). Walls are accordingly represented as line segments or planes. *Layout reconstruction* is the task of retrieving the layout from a metric representation of a building and can be performed at room or at floor level, starting from 2D grid maps [4] or from 3D point clouds [5, 6].

2D metric maps are easily available in most robotic applications, thanks to cheap and reliable 2D sensors, like laser range scanners, and to widely used and efficient 2D mapping algorithms [3]. Moreover, indoor robots usually rely on 2D metric maps as they are more robust than 3D point clouds for several tasks [7]

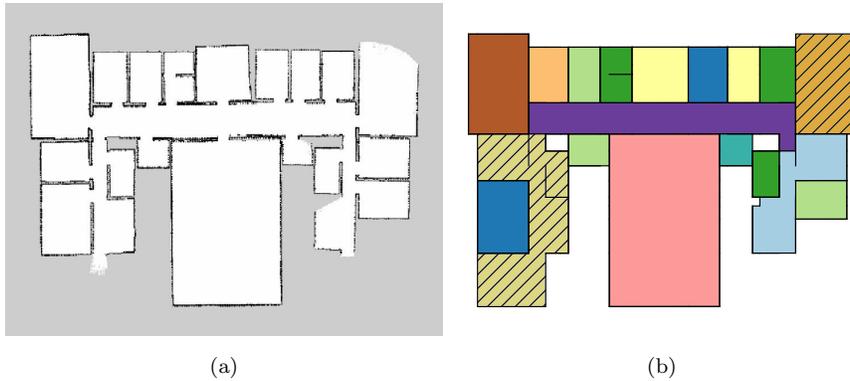


Figure 1: An example of a layout returned by our method. Figure 1a shows a metric map of a simulated large-scale building, where some rooms have been only partially observed by the robot. Figure 1b displays the retrieved layout we obtained from that map, where shapes of fully-observed rooms are shown with solid colors and predicted shapes of partially-observed rooms are shown with dashed-color patterns (bottom-left and top-right).

30 and can deal better both with large-scale buildings and with some types of maps, like maps of partially observed environments incrementally built during exploration. Such partial maps are particularly critical, as they are often the only type of knowledge available online to a robot during exploration. However, the knowledge about the structure of buildings that could be extracted from

35 2D metric maps is more limited than that obtainable from 3D point clouds, where walls, ceilings, and doors are usually easier to identify. Therefore layout reconstruction is usually performed starting from 3D point clouds and this reduces the applicability of layout reconstruction methods. The use of 2D metric maps could potentially smooth such limitation, but it requires to adapt layout

40 reconstruction techniques to the more challenging input of 2D metric maps.

In this paper, we address the above issue by presenting a method that retrieves the layout of indoor environments starting from their 2D metric maps, in order to extend the applicability of layout reconstruction methods. Specifically, our method reconstructs the layout of the parts of the environment that

45 have been fully observed by the robot and, most significantly, *predicts* a possible

layout for the parts of the environments that have been only partially observed by the robot. An example of a layout returned by our method starting from a partially observed metric map is shown in Figure 1.

Our method does not need some of the requirements needed by most methods
50 that deal with 3D point clouds for layout reconstruction, like perfect alignment between scans and precise knowledge of their poses [6]. These requirements are hard to satisfy for metric maps built by mobile robots using 2D laser range scanners and SLAM algorithms [3]. These maps usually present several inaccuracies that our method can address, such as partial, missing, unaligned, and
55 noisy data.

In a nutshell, our proposed method identifies the *representative lines* along which the walls of a building are aligned and uses these lines to segment the area in smaller parts, called *faces*, which are finally clustered in rooms. The representative lines allow to find regularities between different parts of the same
60 building; for instance, two rooms placed at the opposite sides of the building can have aligned walls or a long corridor can connect rooms with the same shape and sharing the same wall. These regularities, extracted from the known parts of the environments, are exploited to predict a possible layout for partially observed rooms.

Our approach is experimentally validated in an extensive range of settings,
65 showing that it performs well with different metric maps provided as input and with metric maps representing environments at different degrees of completeness.

The availability of a layout, like that returned by our method, is useful in
70 several robot applications. For instance, a vacuum-cleaner or a service robot can benefit from planning efficient paths in an abstract representation of the environment and adjusting them during actual motion. Moreover, the computing time of our method (few seconds) allows its use in the online process of exploration of unknown indoor environments [8, 9], in which the robot decision-
75 making about where to move next is performed at a low frequency, as the robot has to physically move around the environment. We explicitly remark that

applying the proposed method to specific settings is beyond the scope of this paper.

This paper is organized as follows. The next section surveys the related work.
80 Section 3 presents the proposed method, which operates in two sequential steps: reconstruction of the layout of the fully observed parts of the environment (Section 3.1) and prediction of a possible layout of the partially observed parts of the environment (Section 3.2). Section 4 discusses the results of the experimental activities performed to evaluate the proposed method. Finally, Section 5
85 concludes the paper.

Preliminary versions of the methods of Sections 3.1 and 3.2 appear in [10] and [11], respectively. This paper originally presents a more coherent view of the two methods and introduces some enhancements in the algorithms (for clustering line segments and for determining the candidate faces) that slightly
90 improve the identification of walls and rooms in partially observed environments. Moreover, we re-implemented the methods and reduced computing times by performing code-level optimizations and by parallelizing and embedding our system into a ROS-based framework. This allowed the online use of our approach in an exploring mobile robot (Section 4.5). Finally, this paper presents several
95 further experimental results, including those on maps built by real robots, that show the ability of the proposed method to reconstruct and predict the layout of buildings.

2. Related Work

Automatic analysis of representations of floors of buildings in order to ex-
100 tract structural information is an interdisciplinary topic addressed in different research fields, such as robotics, architecture, computer vision, and image analysis. While an exhaustive survey is out of the scope of this paper, here we discuss a significant sample of methods, focusing on those developed for mobile robots.

Room segmentation methods typically start from 2D metric maps obtained
105 from laser range scanners and separate them into parts, each one correspond-

ing to a different room. Authors of [1] present a survey of room segmentation techniques for mobile robots. They identify four main families of approaches, namely Voronoi-based partitioning [12], graph partitioning [13], feature-based segmentation [14, 15, 16], and morphological segmentation [17]. Representative
110 methods of the four families are compared in [1] with no method clearly outperforming the others, although Voronoi-based segmentation techniques appear to be the most accurate.

A system for room segmentation that shares some similarities with our layout reconstruction approach can be found in [18]. Similarly to our method, Canny
115 edge transform and Hough line transform are used to extract lines from a grid map. The main difference wrt our method is that, while we extract a relatively small set of representative lines that are used for identifying walls, in [18] a larger set of lines are used for obtaining a scalable grid representation of the environment, similar to an octomap and called *A-grid*, which is eventually used
120 to perform segmentation. Moreover, differently from our method, that of [18] does not perform layout reconstruction but room segmentation.

In general, our approach differs from room segmentation methods, which typically partition the metric maps in rooms, because it extracts from the metric map a more abstract representation in which rooms are modeled using geometric
125 primitives. In our layout representation, a room is a polygon, while, in room segmentation, a room is a set of cells of the grid map. One could say that layout reconstruction provides a more abstract representation of the structure of a building that does not have to be metric exact. Although it is possible to recover the polygon representing a room from the set of cells associated with that room [6] (i.e., as a post-processing of room segmentation), this is
130 largely based on information local to the rooms, hardly capturing global regular features, like alignment of rooms along a corridor, which our approach is able to consider. Most of the methods that perform layout reconstruction require aligned 3D point clouds and usually exploit the knowledge of the poses from
135 where the scans are taken. Our method is inspired by such approaches, but it is adapted to be used on 2D maps obtained by a mobile robot. More precisely,

we extend and adapt the method presented in [6], as explained extensively in Section 3.

Authors of [5] segment and reconstruct rooms of an indoor environment from a 3D point cloud perfectly aligned to a coordinate system. Points are projected on the 2D plan, in order to find walls as sets of points whose projections are close to each other. The entire floor is segmented in areas using these projections of walls. Areas that are adjacent but not separated by a “peak-gap-peak” pattern in the projected points distribution are merged in the final segmentation.

In [19], wall lines are retrieved from an analysis of the distribution of points of a 3D point cloud projected on a 2D plane along the z axis. The structure is then decomposed into its horizontal and vertical parts, which are used to extract a volumetric model through an energy minimization problem solved by a Graph-Cut method.

Two methods that are based on aligned 3D point clouds are presented in [20] and [21]. In [20], 3D point cloud scans (and their poses) are used to recover the 3D model of a building. Walls are detected by projecting on a plane the wall surfaces perceived in different rooms. Similarly to our approach, walls are used for dividing the space. In particular, wall lines are used to reconstruct a planar graph that is later segmented into different rooms by an energy minimization approach. A similar, but improved, method is presented in [21]. It projects a 3D point cloud on a 2D plane to retrieve walls. The 2D map is segmented into rooms by identifying doors/openings along walls and by selecting a set of viewpoints from the Voronoi graph built on the 2D projection. Finally, rooms are found by solving an energy minimization problem on a cell planar graph obtained from the lines of the wall segments. Viewpoints are used to initialize the graph potentials following the intuition that points that can be seen from the same viewpoint are more likely to be part of the same room.

Similarly to our work, [4] proposes a method that segments a 2D metric map of an indoor environment built by a robot while reconstructing its layout. It uses a framework based on Markov Logic Networks and data-driven Markov Chain Monte Carlo (MCMC) sampling. Using MCMC, the system samples

many possible semantic worlds (layouts of the environment) and selects the one that best fits the sensor data. Differently from our work, which identifies the building structure by analyzing the entire metric map, each transition from a state to another state in the MCMC is based on local edit operations on the layout of a single room, ignoring other parts of the building.

All the above methods are able to reconstruct the layout of observed parts of the environments. The goal of obtaining knowledge on unobserved parts of environments has recently been addressed using heterogeneous approaches. In [22], the metric map perceived by the robot is augmented with knowledge of previously observed environments. The parts of the metric map that correspond to portions of the environment that have not yet been observed are completed by superimposing matching maps from a database of previously observed environments. The resulting map is used for predicting loop closures. In a similar way, the method of [23] first predicts the perimeter of the unobserved space and then uses a library of map structures to predict the inner unknown parts of a map while it is built by a team of robots. While the above methods rely on the presence of libraries of environments observed in the past, our approach can be applied also when such data are not available.

A method that shares some similarities with our approach is proposed in [24], which predicts the structure of an unexplored region of an environment to improve SLAM performance. The method starts from a frontier between known and unknown regions and tries to reconstruct its neighbourhood by identifying similar structures in the known map. If a match is found, the matching portion of the map is superimposed to the frontier, thus providing an estimate of the structure of its neighbourhood. There are also mechanisms that avoid the use of inaccurate predicted knowledge that could compromise the robot behaviour. The prediction of [24] considers the similarity between different parts of the same environment (a prediction is made if a part of the map which can constitute a good match to complete a frontier is found), while in our approach we consider more abstract features like the fact that rooms aligned along the same corridor share the same wall.

Some methods have been recently proposed to predict the presence of specific
 200 elements in the unknown parts of environments. For instance, the method of [25]
 trains, from a set of images representing floor plans of buildings, a convolutional
 neural network that is able to predict, given the partial map of an environment,
 the location of an emergency exit. In this context, only one structural feature
 of the environment is extracted explicitly (the position of the emergency exit).
 205 The system proposed in [26] predicts the existence of a room (and its label) in
 the unexplored space, but it does not provide any information on the geometry
 of the room. Similarly, the approach of [27] predicts the topology and the labels
 of unvisited rooms by matching the known part of the environment (represented
 as a labeled graph) to a database of environments. Also [28] predicts portions
 210 of environments represented as graphs using a method based on graph kernels.
 Finally, an interesting integration between metric maps and natural language is
 proposed in [29] in order to infer the existence (in the maps) of spatial elements
 that are mentioned in some sentences.

3. Our Method for Retrieving the Layout from Metric Maps

The method we propose in this paper starts from a 2D metric map, like
 a grid map, identifies the walls in it, and uses them for finding rooms and for
 reconstructing and predicting the 2D layout of the environment. More precisely,
 given a metric map M of an indoor environment, our goal is to retrieve its layout
 \mathcal{L} :

$$\mathcal{L} = \{r_1, \dots, r_n\},$$

215 where r_i is the layout of a room, namely the polygon representing the room.
 Our method is designed to work both with fully observed rooms, whose layout
 is reconstructed, and with partially observed rooms, for which our method is
 able to predict a possible layout for the entire rooms. Hence, the layout \mathcal{L} could
 be partitioned in the layout of the set of fully observed rooms \mathcal{L}_C and in the
 220 layout of the set of partially observed rooms \mathcal{L}_P . In case of a complete metric
 map M , we have that $\mathcal{L}_P = \{\}$.

The method is composed of a number of steps executed sequentially. At first, the method reconstructs the layout \mathcal{L}_C of fully observed rooms. This part is described in Section 3.1. After that, our method predicts a possible layout \mathcal{L}_P for the partially observed rooms, leveraging the information from \mathcal{L}_C and following the intuition that the structural features identified in \mathcal{L}_C are also common to partially observed rooms, as the fact that a wall could be shared by multiple rooms. This second step is described in Section 3.2. As discussed in the introduction, preliminary versions of the methods of Sections 3.1 and 3.2 appear in [10] and [11], respectively.

3.1. Reconstructing the layout of fully observed rooms

In this section we describe our approach for reconstructing the layout \mathcal{L}_C of fully observed rooms with the help of a running example (Figure 2). We thus assume to start from a fully known metric map M .

Some of the steps of our method (Algorithm 1) are inspired by the approach of [6]. More precisely, we use the method developed in [6] for dividing the metric map into smaller parts (which are used to identify rooms) using a set of lines. However, as already discussed, [6] reconstructs the 3D layout of a building from point clouds precisely aligned and registered in the same coordinate system, knowing the number and the poses of scans. Differently from [6], our method is intended to be used on 2D metric maps obtained from data acquired by laser range scanners and processed by SLAM algorithms, which can present misalignments and artefacts. Moreover, our method can be used effectively on different types of metric maps obtained from different sources, such as incomplete metric maps, blueprints, and evacuation maps, as described in Section 4.

The starting point is a metric map M representing an indoor environment, typically a floor of a building. Without loss of generality, we assume that M is a 2D grid map, like the one in Figure 2a, namely a two-dimensional matrix of cells (pixels), each one representing the probability that the corresponding area is occupied by an obstacle.

The first operation on M is the detection of significative edges using the

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Input: a grid map  $M$ 
Output: the reconstructed layout  $\mathcal{L}_C$ 

/* Compute features from the map */
 $M' \leftarrow \text{CannyEdgeDetection}(M)$ 
 $S \leftarrow \text{pHoughLineTransform}(M')$ 

/* Obtain contour of the map */
 $M'' \leftarrow \text{thresholdMap}(M, q)$ 
 $Inner \leftarrow \text{computeMapContour}(M'')$ 

/* Create clusters of collinear segments */
 $C \leftarrow \text{meanShiftClustering}(S)$ 
 $\mathcal{W} \leftarrow \text{spatialClustering}(C, wall)$ 

/* Find faces from representative lines */
 $lines \leftarrow \text{getsRepresentativeLines}(\mathcal{W})$ 
 $F \leftarrow \text{findFaces}(lines)$ 

/* Compute spatial affinity between faces */
 $L \leftarrow \text{computeAffinityMatrix}(F)$ 
 $D \leftarrow \text{diag}(\sum_{j=1}^n L_{i,j})$ 
 $A \leftarrow D^{-1}L$ 

/* Remove external faces outside border */
for  $f \in F$  do
  if  $\text{area}(f \cap Inner) < \delta$  then
     $F \leftarrow F \setminus f$ 
  end
end

/* Remove partially observed faces */
for  $f \in F$  do
  if  $\text{containFrontier}(f)$  then
     $F \leftarrow F \setminus f$ 
  end
end

/* Cluster together faces into rooms */
 $\mathcal{L}_C \leftarrow \text{DBSCAN}(F, A, \epsilon, \text{minPoints})$ 
return  $\mathcal{L}_C$ 

```

Algorithm 1: Our method for layout reconstruction of fully observed rooms.

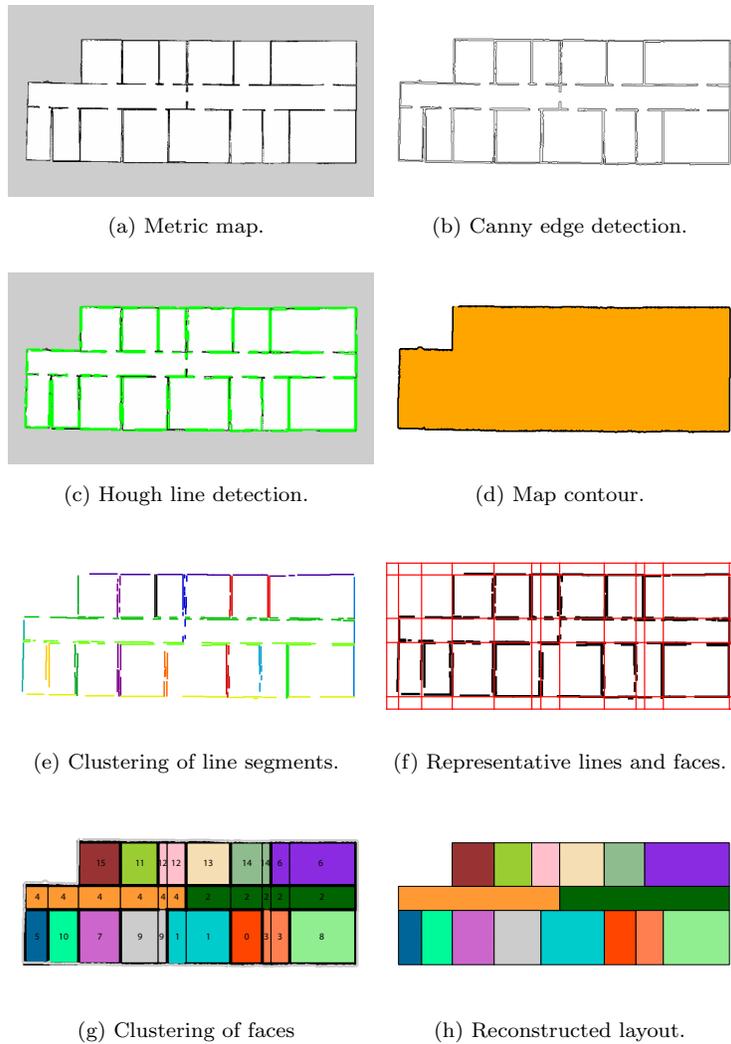


Figure 2: An example run of our method to reconstruct the layout from a complete metric map.

Canny edge detection algorithm [30], which partitions the cells of M into free cells and obstacle cells. The binary metric map resulting from the application of the Canny edge detection algorithm is called M' and an example is shown in Figure 2b.

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The set of edges (obstacle cells) is then processed by a probabilistic Hough

line transform algorithm [31] to detect the line segments S that approximate the edges in M' . Figure 2c shows such line segments in green. Note that one of the parameters of the method, *minLinPoints*, represents the minimum number of points that are required for having a line. Then, the contour of the map is obtained, using the contour detection algorithm of [32], after the application of a threshold q that divides cells of the original map M into free or occupied. Figure 2d shows in yellow the area inside the map border.

The line segments S are then clustered together according to the angular coefficients of their supporting lines using the mean shift clustering algorithm [33]. At the end of the angular clustering, we obtain a set of clusters $\mathcal{C} = \{C_1, C_2, \dots\}$ such that each $C_j \subseteq S$ and $C_1 \cup C_2 \cup \dots = S$. Each cluster C_j represents the set of line segments with similar angular coefficient α_j , namely with similar direction, independent of their spatial proximity.

Next, the line segments belonging to the same angular cluster C_j are further clustered in sets of collinear walls by grouping those line segments that are close to each other. Specifically, line segments of C_j are partitioned in sets $W_{j,k}$. This spatial clustering is performed using DBSCAN [34] with the smallest distance between any two points of two line segments s and s' as metric. (We set the two DBSCAN parameters to $\epsilon = 0.75$ and *minPoints*= 2.) Each line segment in C_j is thus assigned to a cluster $W_{j,k}$, which represents a wall.

Collinear walls are further joined if the line segments composing them are close enough. The distance between two walls is computed as follows. Given a wall $W_{j,k}$, one of its line segments $s_{j,k}$ is selected as that with the median middle point (along a direction perpendicular to α_j). Now, given two walls $W_{j,k}$ and $W_{j,k'}$, call l and l' the parallel lines passing through the middle points of $s_{j,k}$ and $s_{j,k'}$, both with angular coefficient α_j . If the distance between l and l' is less than a threshold *wall* (intuitively, closer than the width of a doorway), then the two corresponding walls $W_{j,k}$ and $W_{j,k'}$ are merged together. At the end of this step, the set of clusters $\mathcal{C} = \{C_1, C_2, \dots\}$ is thus further partitioned into a set of clusters $\mathcal{W} = \{W_{1,1}, W_{1,2}, \dots, W_{2,1}, W_{2,2}, \dots\}$, such that $C_1 = W_{1,1} \cup W_{1,2} \cup \dots$ and $C_2 = W_{2,1} \cup W_{2,2} \cup \dots$, and so on. Figure 2e shows the results of the

spatial clustering where the line segments belonging to the same cluster in \mathcal{W} are displayed with the same color.

290 At this point, for each cluster $W_{j,k}$, a *representative line* $l_{j,k}$ that represents all the line segments in $W_{j,k}$ is determined. This representative line is computed as the line with angular coefficient α_j associated to C_j and that passes through the median of the set of middle points of the line segments in $W_{j,k}$. Each representative line, in red in Figure 2f, indicates the direction of a wall within
295 the building. The intersections between all lines induce a tessellation of the metric map that divides the area of the map M' into different polygonal areas, called *faces*, as shown in Figure 2f. We call F the set of faces. Note that, as visible in Figure 2f, our method uses a relatively small number of representative lines for segmenting the environment, as line segments found in the metric map
300 are hierarchically clustered together. This allows us to consider a small number of primitives in the environment (line segments and faces) in order to capture regularities in the metric map. For example, in our method, collinear walls which are slightly distorted and tilted due to map inaccuracies are not represented by different representative lines close to each other, as in [18, 21], but are considered
305 as a single representative line. In this way, our method provides a more abstract representation of the environment that is used for layout reconstruction. In order to handle partially observed rooms (see next section) whose frontiers are not bounded by any representative line, we pad the map M with an additional set of representative lines that form a bounding box of M slightly larger than
310 the actual size of the map contour.

Rooms are determined by grouping faces together. Adjacent faces that are separated by an edge corresponding to a wall should belong to different rooms, while adjacent faces that are separated by an edge not corresponding to any wall should be grouped together in the same room. More precisely, for each pair of faces f and f' that share a common edge $e_{f,f'}$ (belonging to the representative line $l_{j,k}$ of a spatial cluster $W_{j,k}$), we compute a weight $w(e_{f,f'})$ as follows (as

in [6]):

$$w(e_{f,f'}) = \frac{cov(e_{f,f'})}{len(e_{f,f'})},$$

where $len(e_{f,f'})$ is the length of $e_{f,f'}$ and $cov(e_{f,f'})$ is the length of the projections, on $e_{f,f'}$, of the line segments in $W_{j,k}$. The larger the weight $w(e_{f,f'})$, the stronger the hypothesis that there is a wall (obstacle) along $e_{f,f'}$ (namely, between faces f and f'). If an edge is completely covered by projections of line segments in $W_{j,k}$, then its weight is 1. Following the definition of [6], weighted edges are used to compute an affinity measure L between all pairs of faces. L is similar to a Laplacian, and its entries $L_{f,f'}$ are defined as:

$$L_{f,f'} = \begin{cases} e^{-w(e_{f,f'})/\sigma} & \text{if } f \neq f' \text{ and } f \text{ and } f' \text{ are adjacent} \\ 1 & \text{if } f = f' \\ 0 & \text{otherwise} \end{cases},$$

where σ is a regularization factor. From the matrix L , a local affinity matrix A is defined as $A = D^{-1}L$, with $D = diag(\sum_{j=1}^n L_{i,j})$, where n is the number of faces in F and i is the row of the matrix. Each element $A_{f,f'}$ indicates an affinity value considering the local connectivity between faces f and f' . The
315 matrix A is used as input for DBSCAN, which clusters faces. DBSCAN groups together those faces that are close to each other in a dense portion of the feature space represented by matrix A . (In our experiments, we set the two DBSCAN parameters to $\epsilon = 0.85$ and $minPoints = 1$.) Note that DBSCAN detects rooms without any additional information, while the method of [6] relies on the avail-
320 ability of scan poses. In this sense, our approach can flexibly adapt to different input sources for metric maps, as shown in the next section.

Before applying DBSCAN, some faces are discarded. Specifically, discarded faces are those called *external* and such that the area of their intersection with the inner area of M (obtained from the contour) is smaller than a threshold δ .

325 Then, DBSCAN is applied to internal faces to obtain a set of clusters $R = \{F_1, F_2, \dots\}$ of F . Each cluster F_i corresponds to a room r_i , which is represented as a polygon obtained by merging together all the faces belonging

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Input:  $M, \mathcal{L}_C, F, lines$ 
Output: the predicted layout  $\mathcal{L}_P$ 

/* Get partial rooms */
 $P \leftarrow FindPartialRoomsFromFrontiers(M, F, \mathcal{L}_C)$ 
/* Get candidate faces */
for  $r_i \in P$  do
    /* Find initial layout composed of already observed faces */
     $\hat{F}'_i \leftarrow getObservedFacesInRoom(r_i, M, P, F)$ 
     $r'_i \leftarrow \hat{F}'_i$ 
    /* Evaluate best layout among all possible sets of faces */
    for  $\hat{F} \in \mathcal{F}$  do
        if  $\Phi(\hat{F} \cup F'_i) \geq \Phi(r'_i)$  then
             $r'_i \leftarrow \hat{F} \cup F'_i$ 
        end
    end
    /* Update map and set of faces after new predicted room */
     $\hat{r}_i^* \leftarrow r'_i$ 
     $\mathcal{L}_P \leftarrow \mathcal{L}_P \cup \hat{r}_i^*$ 
     $\mathcal{F} \leftarrow \mathcal{F} \setminus (\hat{F} \cup F'_i)$ 
end
return  $\mathcal{L}_P$ 

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Algorithm 2: Our method for predicting the possible layout of partially observed rooms.

to F_i . Figure 2g shows the results of DBSCAN for our example. The number i in each face indicates its cluster F_i . Different clusters have also different colors.

330 The final reconstructed layout $\mathcal{L}_C = \{r_1, r_2, \dots\}$ is finally displayed in Figure 2h. Note that it is a “clean” and abstract representation of the original grid map of Figure 2a, which nevertheless retains the main structural features.

335 A side effect of our proposed method is that it could happen that gaps inside buildings are wrongly identified as rooms. However, such rooms are disconnected from the rest of the environment and can be easily filtered out. A post-processing refinement could be used to remove unconnected rooms when connectivity between rooms (e.g., doorways) is known, like when the input metric map comes from a blueprint.

3.2. Predicting the layout of partially observed rooms

340 In this section, we illustrate our method that predicts a possible layout of partial rooms in \mathcal{L}_P , namely of those rooms that have not been fully observed by the robot sensors (Algorithm 2).

The input metric map M , in this case, is partial, and does not represent the entire environment. In a partial metric map, *frontiers* can be identified as
345 the boundaries between known and unknown space. For example, in a partial grid map in which cells can be either known or unknown and known cells can be either free or obstacles, a frontier cell is a free cell that is adjacent to an unknown cell, while a frontier is a chain of adjacent frontier cells.

To account for the fact that the initial grid map M is partial, before faces
350 are clustered in rooms (last step of Algorithm 1), *partial faces* are recognized as faces that contain a frontier and are excluded from the process that brings to identify $\{F_1, F_2, \dots\}$. After clustering, if a room r_i has faces in F_i that are adjacent to partial faces (with the common edge not being a wall), it is considered a *partial room*. Also partial faces that are not adjacent to any F_i are
355 clustered to form additional partial rooms. The set of partial rooms is called P .

The main idea of our method is that the structure of a partial room shares some features with the structure of the part of the environment that is known. For example, the external walls of a building are shared by several rooms and the rooms along a corridor have a similar shape. Our method considers the
360 partial rooms of P in sequence (a random sequence is fine since each partial room is processed independently) and, for each partial room, it completes its layout by predicting the unknown part of the room still to be observed by the robot. In practice, given a partial room $r_i \in P$, some (unobserved) faces are added to the (observed) faces in F_i in order to maximize an objective function
365 that represents how well the new layout \hat{r}_i consistently matches with that of the known part of the environment.

In detail, given a partial room $r_i \in P$ with fully observed faces F_i (obtained as described in the previous section), our method first adds to F_i the partial faces that contain a frontier and that are adjacent to at least one face in F_i

370 (and with the common edge not corresponding to a wall), obtaining a set of faces $F'_i \supseteq F_i$.

Then, F'_i is further enriched with a set of faces \hat{F}_i^* , the predicted layout \hat{r}_i^* of partial room r_i is obtained from merging faces in $F'_i \cup \hat{F}_i^*$, and \hat{r}_i^* is added to \mathcal{L}_P . \hat{F}_i^* is selected from a family \mathcal{F} of candidate sets of faces (also including the
375 empty set). A candidate set of faces $\hat{F} \in \mathcal{F}$ satisfies the following conditions:

- (1) \hat{F} contains faces adjacent to faces of F'_i or adjacent to faces which are in turn adjacent to faces in F'_i (namely, at most “two hops” away from faces in F'_i);
- (2) \hat{F} contains faces not adjacent to the external contour of the map;
- 380 (3) \hat{F} contains faces not “behind” any of the walls that have already been observed for the room r_i .

Condition (1) limits the number of sets in \mathcal{F} ; conditions (2) and (3) keep the prediction of the layout of a room consistent with what has been observed. \hat{F}_i^* is chosen from \mathcal{F} to maximize an objective function:

$$\hat{F}_i^* = \arg \max_{\hat{F} \in \mathcal{F}} \Phi(F'_i \cup \hat{F}),$$

385 where $\Phi()$ is a weighted sum of three components:

$$\Phi(F'_i \cup \hat{F}) = k_{\Upsilon} \cdot \Upsilon(F'_i \cup \hat{F}) - k_{\Psi} \cdot \Psi(F'_i \cup \hat{F}) - k_{\Omega} \cdot \Omega(F'_i \cup \hat{F}).$$

Note that we evaluate a candidate \hat{F} by considering the set of faces $F'_i \cup \hat{F}$ and the corresponding layout \hat{r}_i . See Figure 3 for an example.

The first term of the objective function, $\Upsilon()$, embeds the intuition that the predicted layout \hat{r}_i should be consistent with that of known rooms. The
390 quantitative evaluation of this consistency is done by resorting to the representative lines. For example, if $l_{j,k}$ represents a wall along a long corridor, it will be common to all the rooms that are connected to that corridor. Thus, the same wall will delimit the partial rooms connected to the same corridor. Given a representative line $l_{j,k}$, we consider in turn all the line segments s of

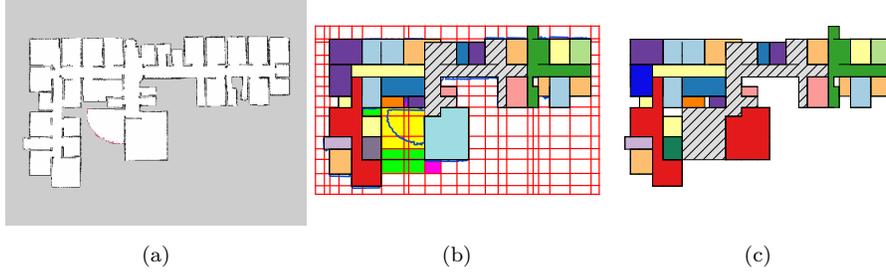


Figure 3: Figure 3b shows an example of prediction of the layout of partial rooms: faces in the two selected $F'_i \cup \hat{F}_i^*$ are in yellow, faces belonging to other candidate sets \hat{F} are in green, faces excluded from candidate sets \hat{F} due to conditions (1)-(3) are in fuchsia. Figure 3a shows the map M and Figure 3c the reconstructed layout.

395 the associated cluster $W_{j,k}$, we project them on $l_{j,k}$, and we compute a weight
 $\bar{w}(l_{j,k}, s) = \text{cov}(s, l_{j,k}) / \text{len}(l_{j,k})$, where $\text{cov}(s, l_{j,k})$ is the length of the projec-
tion of s on $l_{j,k}$, and $\text{len}(l_{j,k})$ is the length of the segment of $l_{j,k}$ that is inside
the contour of the map M . We then call \hat{L} the set of representative lines that
would be the boundaries of room \hat{r}_i if \hat{F} is selected to complete the room, finally
400 computing:

$$\Upsilon(F'_i \cup \hat{F}) = \sum_{l_{j,k} \in \hat{L}} \sum_{s \in W_{j,k}} \bar{w}(l_{j,k}, s).$$

The second term of the objective function, $\Psi()$, is designed in order to prefer simple (predicted) layouts over complex ones. This is done by computing the convex hull of the layout \hat{r}_i in case \hat{F} is added to F'_i . Calling $\text{area}()$ the operator that computes the area of a polygon and $\text{hull}()$ the operator that computes the convex hull of a polygon:

$$\Psi(F'_i \cup \hat{F}) = \frac{\text{area}(\text{hull}(\hat{r}_i)) - \text{area}(\hat{r}_i)}{\text{area}(\hat{r}_i)}.$$

The third term of the objective function, $\Omega()$, prefers the layouts that are delimited by a small number of walls. This is done by counting the number $\text{nw}_{\hat{r}_i}$ of walls of \hat{r}_i , namely the number of external edges of the faces in $F'_i \cup \hat{F}$ that lie on different representative lines, thus having $\Omega(F'_i \cup \hat{F}) = \text{nw}_{\hat{r}_i}$.

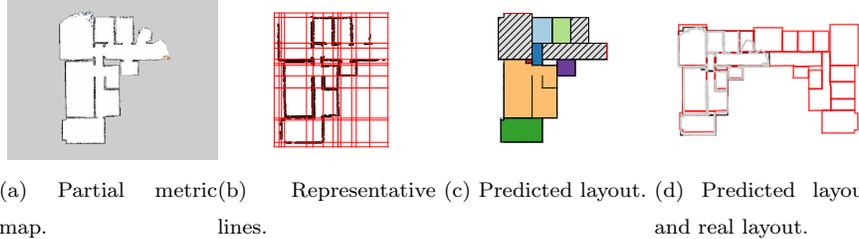


Figure 4: An example run of our approach starting from a partial grid map with predicted layout of partially observed rooms (dashed) and an open frontiers (red). Figure 4d shows the map perceived by the robot (gray), the layout predicted by our method (black), and the actual layout of the building (red).

405 Figure 4 shows an example that illustrates the proposed method for the prediction of the layout of three partial rooms. The predicted layout of the partial rooms is dashed in Figure 4c. In our experiments, we set $k_\gamma = 1$, $k_\Psi = 5$, and $k_\Omega = 0.1$ (these values have been selected after several preliminary trials).

410 A particular situation is encountered when a partial room is at the border of the map M . In this case, one or more sides of the room are not bounded by any representative line derived from the known map and the layout of the room cannot be predicted. When this happens, we label the room as containing an *open frontier* and we highlight the corresponding edges in red, as in Figure 4.

415 Before starting the prediction of the layout of partially observed rooms, a pre-processing step is applied to \mathcal{L}_C in order to reduce under- and over-segmentation of rooms. These two issues are caused when two (or more) rooms are wrongly considered as a single entity (under-segmentation) or when a large room is incorrectly split in several smaller rooms (over-segmentation). (See the next section for details.) If the portion of a room observed by the robot is very small, as when the robot passes in front of a doorway without going inside the room, under-segmentation is very likely. A Voronoi graph obtained from M is used to split (likely under-segmented) rooms divided by a doorway, following the approach presented in [1]. Over-segmentation is instead addressed by using the

425 approach proposed as post-processing in [6] that merges two adjacent rooms for which the following function Q_{split} returns a value larger than a threshold $\tau = 0.2$:

$$Q_{split}(\mathcal{B}) = \frac{\sum_{i=1}^n w(e_i) * len(e_i)}{\sum_{i=1}^n len(e_i)},$$

where $\mathcal{B} = \{e_1, \dots, e_n\}$ is the set of edges common to those two rooms and $w(e_i) = cov(e_i)/len(e_i)$ as defined in Section 3.1.

430 4. Experimental Results

In this section, we evaluate our method for reconstructing and predicting the layout of buildings from 2D metric maps.

A reconstructed (or predicted) layout is expected to present two main characteristics: (1) all the rooms of the real building (and only them) should be
 435 in the layout; (2) the shape of each room in the layout should match that of its real counterpart. Evaluation is performed both visually and quantitatively, comparing the reconstructed or predicted layout \mathcal{L} and the ground truth layout Gt . Following the approach of [1], we introduce two matching functions between rooms in \mathcal{L} and in Gt (after \mathcal{L} and Gt have been aligned), namely
 440 *forward coverage* FC and *backward coverage* BC :

$$FC : r \in \mathcal{L} \mapsto r' \in Gt \quad BC : r' \in Gt \mapsto r \in \mathcal{L}.$$

For each room $r \in \mathcal{L}$, FC finds the room $r' \in Gt$ that maximally overlaps r ; conversely, for each room $r' \in Gt$, BC finds the room $r \in \mathcal{L}$ with the maximum overlap with r' . Recalling that $area()$ is a function that computes a polygon area, the amount of overlap between a room $r \in \mathcal{L}$ and a room $r' \in Gt$ is
 445 defined as $area(r \cap r')$.

Matching functions FC and BC are used for computing two measures of accuracy called *forward accuracy* A_{FC} and *backward accuracy* A_{BC} :

$$A_{FC} = \frac{\sum_{r \in \mathcal{L}} area(r \cap FC(r))}{\sum_{r \in \mathcal{L}} area(r)} \quad A_{BC} = \frac{\sum_{r' \in Gt} area(BC(r') \cap r')}{\sum_{r' \in Gt} area(r')}.$$

A_{FC} represents how well the reconstructed layout \mathcal{L} is described by the ground truth layout Gt , while A_{BC} represents how well the ground truth layout Gt is described by the reconstructed layout \mathcal{L} . The numbers of rooms in \mathcal{L} and Gt can be different, due to over- or under-segmentation. Over-segmentation results in high A_{FC} and low A_{BC} , while under-segmentation results in high A_{BC} and low A_{FC} .

We evaluate separately the performance of reconstructing the layout \mathcal{L}_C of fully observed rooms and of predicting the layout \mathcal{L}_P of partially observed rooms. Recall that our method reconstructs \mathcal{L}_C and uses it to predict the layout \mathcal{L}_P ; hence, the quality of \mathcal{L}_C affects that of \mathcal{L}_P .

Our method could be used online for supporting the execution of other tasks of autonomous mobile robots (Section 4.5). The computation of \mathcal{L} takes few seconds for small metric maps and less than 10s even for large metric maps (to compute both \mathcal{L}_C and \mathcal{L}_P). The method is run in a dedicated ROS node so that an updated version of \mathcal{L} is always available for potential use without introducing delays.

4.1. Evaluation of layout reconstruction of fully observed environments

We consider 20 2D grid maps obtained running the ROS implementation¹ of the GMapping algorithm [35] on data collected by a robot equipped with a laser range scanner and moving autonomously in 20 large-scale buildings simulated in Stage². Buildings range from 1000 m² to 3500 m² in size and represent real-world school buildings. The same 20 input maps are considered for evaluating our method both for reconstructing the layout of fully observed rooms (in this section) and for predicting the layout of partially observed environments (Section 4.4). In the former case, we consider complete maps at the end of data collection runs, while, in the latter case, we evaluate our method using partial maps at different stages of data collection runs. More details are provided in

¹<http://wiki.ros.org/gmapping>

²<http://wiki.ros.org/stage>

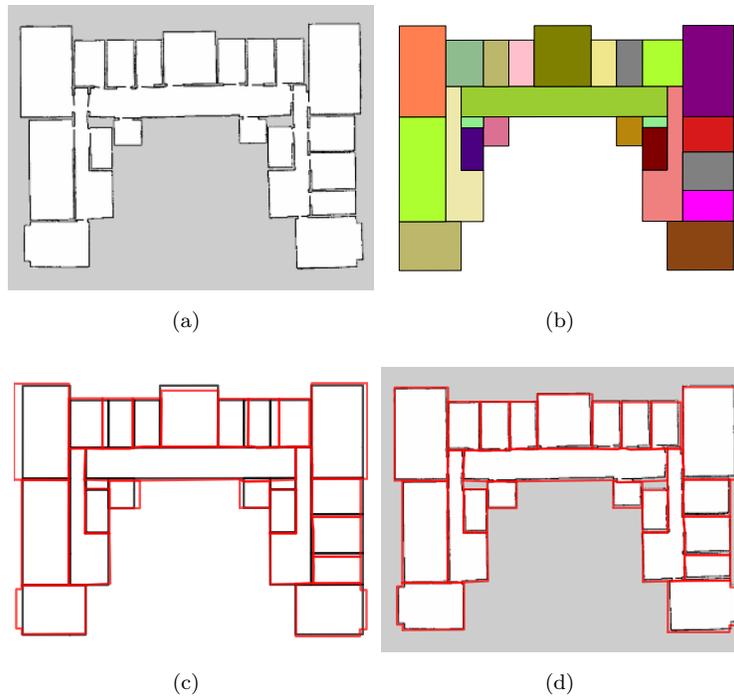


Figure 5: An example of a layout reconstruction. (a) Grid map. (b) Reconstructed layout. (c) Reconstructed layout (black) and ground truth (red). (d) Grid map and ground truth (red).

475 Section 4.4.

It is important to point out that the evaluation is performed by comparing the layouts reconstructed from the grid maps built by the robot against the *actual* layouts of the simulated buildings fed to Stage. This allows us to evaluate if our layout reconstruction approach is able to cope with noise and errors introduced in the mapping process as a result of noisy readings from the sensor, localization errors, or errors due to inaccurate odometry readings. In our simulations, we assume that the robot has a translational odometry error of up to 0.05 m/m and a rotational odometry error of up to $2^\circ/\text{rad}$, which provide a reasonable approximation of the odometry accuracy of real wheeled robots. In this sense, we consider simulated but realistic metric maps obtained by robots.

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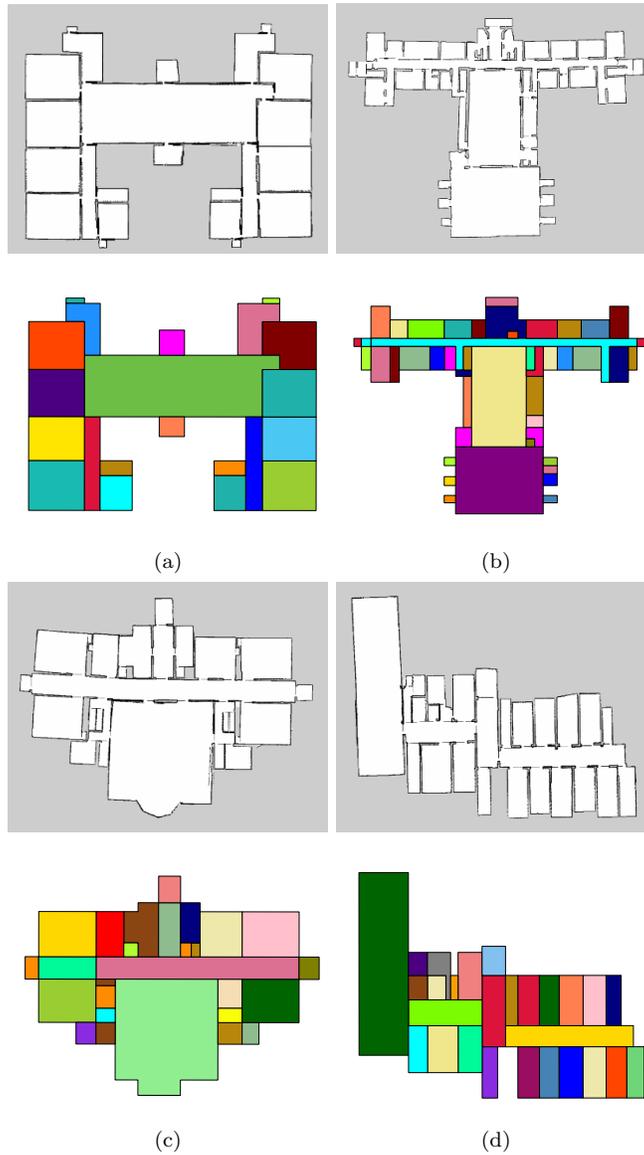


Figure 6: Examples of layout reconstruction.

We note that a comparison of our approach against similar methods such as [6, 20, 21] requires radically different input data (e.g., aligned 3D point scans vs. 2D grid maps) and is not reported here.

Average layout reconstruction accuracies over the 20 grid maps are the fol-

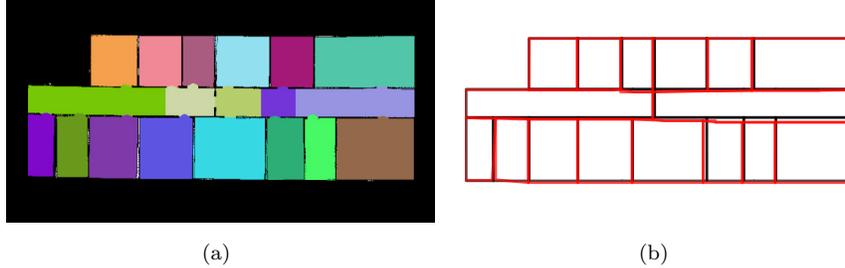


Figure 7: Segmentation by a Voronoi-based approach from [1] (a) and comparison between our reconstructed layout (black) and the ground truth layout (red) (b) for the metric map of Figure 2a.

490 lowing: $A_{BC} = 87.8\% \pm 4.5\%$ and $A_{FC} = 87.6\% \pm 5.7\%$. On the set of 20 environments mapped by the simulated robot, our method is able to reconstruct successfully and with good accuracy the layout of the original buildings. For example, Figure 5 presents a grid map obtained by the robot (Figure 5a) and the layout reconstructed using our method (Figure 5b). For this particular example, we have $A_{FC} = 90.1\%$ and $A_{BC} = 93.3\%$. In Figure 5c, the reconstructed layout (in black) and the ground truth layout (in red) are superimposed. Although the layout is generally accurate, there are small differences in the geometry of rooms, due to approximations introduced by our method, which result in slight performance degradation. In Figure 5d the grid map and the ground truth building layout (in red) are superimposed. While the grid map provides a good representation of the environment, some inaccuracies, such as irregular gaps between walls, are present. Our method tries to filter out those inaccuracies when reconstructing the layout.

Figure 6 shows four other examples of reconstructed layouts from grid maps. In all the four cases, our method is able to correctly reconstruct the layout of the environment, coping well with alignment and rotation errors and with gaps between rooms in the metric maps (e.g., see Figure 6c). Few inaccuracies are introduced, like long corridors split into smaller units, thus producing over-segmentation. Another error is made sometimes when there is a small gap

no furniture		furniture	
recall	90.0% ± 4.1%	recall	89.5% ± 6.2%
precision	90.1% ± 6.3%	precision	94.0% ± 2.2%

Table 1: Layout reconstruction results on datasets from [1].

510 within the building (e.g., due to a large wall or a pillar), which is misclassified as an internal face and subsequently added to an adjacent room or considered as a small independent room. However, in general, our method can successfully retrieve the layouts of large-scale buildings, as in Figure 6b, where the rooms connected to the top corridor (light blue) are the classrooms of a high school.

515 Since walls are represented by straight lines, round walls are approximated by polylines (see Figure 6c). Maps that present (relatively) small misalignments are adjusted by our method, as shown in Figure 6c and 6d. A trade-off exists between the accuracy of alignment that can be reached by our method and its ability to approximate round walls with polylines. This trade-off can be set
520 by modifying the parameters of the line segment clustering step (Section 3.1), like the *wall* threshold, currently set to the width of a doorway, during which collinear walls are clustered together and used to identify representative lines. In all the examples presented in this paper we prefer strong alignment over good approximation of round walls.

525 4.2. Evaluation on publicly available datasets

Here, we present the results of the evaluation of our method for reconstructing the layout of fully observed buildings on the two datasets (each composed of 20 metric maps) used in [1] for comparing different methods for room segmentation. The datasets contain fully observed metric maps with and without furniture, respectively, and, in [1], are evaluated employing precision and recall metrics, which are defined similarly to A_{FC} and A_{BC} :

$$Precision = \frac{\sum_{r \in \mathcal{L}} area(r \cap FC(r)) / area(r)}{|\mathcal{L}|}$$

$$Recall = \frac{\sum_{r' \in Gt} area(BC(r') \cap r') / area(r')}{|Gt|}.$$

When the dataset with furniture is used, our method filters out some of the clutter introduced by furniture by automatically clustering and removing isolated obstacle cells using DBSCAN directly on the original metric map M (this is a very simple way to handle furniture, which can be definitely improved). Results, reported in Table 1, are good and confirm those obtained with our dataset.

A comparison with the results obtained by room segmentation methods of [1] is unfair, because those methods directly partition the cells of the metric maps, while our method uses a more abstract representation based on representative lines and faces, thus introducing some approximations. An example of the approximations introduced by our layout reconstruction with respect to room segmentation is displayed in Figure 7. Figure 7a shows the Voronoi-based segmentation of the metric map of Figure 2a, as reported in [1]. It can be observed that Voronoi-based methods tend to produce over-segmentation. In Figure 7b, we compare our reconstructed layout (in black) with the real structure of the building (in red). Despite being able to correctly capture the building layout, for this map we have $A_{FC} = 93.6$ and $A_{BC} = 94.6$, due to some visible approximations. That said, comparing Table 1 with Table II of [1], we can say that our method produces results comparable (within 1 sigma) with those of the methods surveyed in [1], further confirming that the reconstructed layout actually captures the structure of the buildings. Moreover, the availability of the layout enables a number of possible tasks, as suggested in the following sections.

Our method does not assume a Manhattan world and can be used in non-Manhattan environments, such as those with diagonal walls. Datasets from [1] feature some non-Manhattan buildings, as the two reported in Figure 8. In Figure 8a-8b, it can be seen how our method approximates round walls with a set of diagonal line segments, as already pointed out in the previous section. An example of reconstruction of the layout of a non-Manhattan building with several diagonal walls is shown in Figure 8c-8d, where the reconstructed layout of the building, despite some inaccuracies due to under-segmentation of the

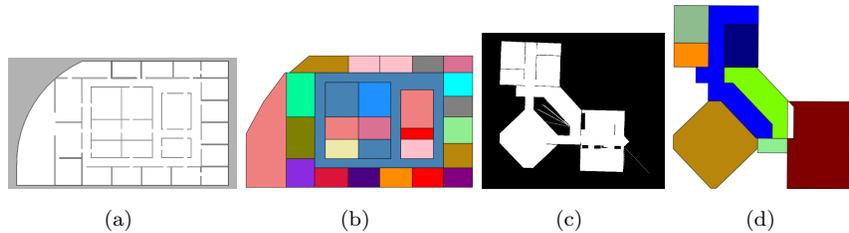


Figure 8: Reconstructed layout from metric maps of non-Manhattan buildings from [1].

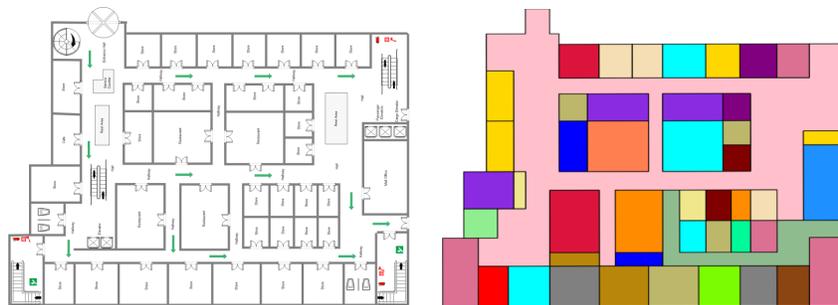


Figure 9: Reconstructed layout from a blueprint of a highly structured building.

555 main central corridor (in blue), is basically correct.

4.3. Evaluation on blueprints and evacuation maps

Our method can be used also for reconstructing the layout of a building from its blueprint or evacuation map. Blueprints and evacuation maps are usually images in which the walls of buildings are represented together with symbols
 560 and words that explain the meaning and the locations of some features (e.g., the functions of the rooms and the presence of fire extinguishers). As blueprints and evacuation maps represent entire floors of buildings, we apply here our method to reconstruct the layout starting from them.

We pre-process these input maps as follows. Words (like the name of the
 565 building or the functions of rooms) are recognized and filtered out using a standard OCR method (Tesseract). Doors and other symbols (like fire extinguishers) are easily retrieved and eliminated, since they are represented with standard

symbols, by using template-matching algorithms. An example of a layout re-constructed from a blueprint is shown in Figure 9. Other examples are reported
570 in our repository³. Quantitative results of layout reconstruction starting from blueprints (and evacuation maps) are similar to those obtained with datasets from [1] and are not reported.

The reconstructed layout of a building obtained from a blueprint can be a useful source of knowledge, especially when the environment in which robots
575 operate is initially unknown, as in a situation where a team of robots performs search and rescue operations and an evacuation map of the environment can be seen on a wall. One of the possible uses of such knowledge is localization, as done in [36], where a robot can localize itself using a floor plan instead of a metric map. A reconstructed layout may introduce some approximations compared to
580 the real shape of the environment, as explained previously. However, [37, 38] show how partially inaccurate hand-drawn sketch maps can be effectively used for robot localization. In principle, using similar approaches, a reconstructed layout of a building can be used for robot localization even if it is slightly inaccurate.

585 4.4. Evaluation of layout prediction of partially observed environments

In this section, we present some of the experimental activities we performed to evaluate our approach for predicting possible layouts of partially observed environments, by trying to complete partial maps acquired during their exploration.

590 As before, the predicted layout of a partial room is evaluated according to how much it matches the actual layout of the room. Evaluation is performed both visually and quantitatively, comparing the reconstructed layout \mathcal{L} and the ground truth layout Gt . For a quantitative evaluation, we adopt a metric different of forward accuracy and backward accuracy used so far, because
595 predicting the layout of partially observed rooms often results in an increase of

³<https://github.com/goldleaf3i/predicted2Dlayout>

under-segmented rooms, since partial rooms where only a small part has been observed are usually under-segmented. Hence, after aligning \mathcal{L} and Gt , given the predicted layout \hat{r}^* of a room in \mathcal{L} , we look for the room r in Gt that maximizes the overlap with \hat{r}^* using the forward coverage function and we compute their *Intersection over Union* (IoU) as:

$$\text{IoU}(\hat{r}^*, r) = \frac{\text{area}(\hat{r}^* \cap r)}{\text{area}(\hat{r}^* \cup r)}.$$

Intuitively, we consider the area $r \setminus \hat{r}^*$ as a false negative, the area $\hat{r}^* \setminus r$ as a false positive, and the area of $\hat{r}^* \cap r$ as a true positive.

Also in the case of partially observed environments, we compare the layouts reconstructed by our method and the actual layouts of the simulated buildings fed to Stage simulator. This allows us to evaluate if our layout prediction approach is able to cope with noise and errors introduced in the mapping process as a result of the imprecise movements of the simulated robot.

We consider the same 20 large-scale school buildings that we used in Section 4.1. For each simulated environment (in Stage), we incrementally map it (with GMapping) following a closest frontier exploration strategy [39]. Since the information we use for prediction comes from the parts of the environment already observed, we expect the quality of our estimate to increase with the amount of information in the grid map M . Consequently, partial grid maps obtained at different stages of exploration are considered. We discard maps from the early stages of exploration (those that covers less than 20% of the area of the environment) because they do not contain enough information for prediction (almost all the frontiers are open frontiers).

A particular case, that happens at final stages of exploration when maps are almost complete, is that of a partial room for which a very small portion, as a corner behind a door, has not been observed. The layout of such room can thus be trivially reconstructed by considering only faces in F'_i (see Section 3.2). Those rooms cannot be expanded anymore since they are usually surrounded by other fully observed rooms and the unobserved portion of their area is usually less than 1 m^2 . We do not consider such rooms in our evaluation because their layout

<i>expl</i>	$\#M$	$ P $	IoU
$\geq 20\%$	196	482	0.70 (0.18)
$\geq 25\%$	173	412	0.72 (0.17)
$\geq 50\%$	100	203	0.75 (0.16)
$\geq 75\%$	25	40	0.82 (0.11)
$\geq 90\%$	18	23	0.86 (0.06)

Table 2: Accuracy (IoU) of our predicted layout obtained incrementally exploring 20 large-scale buildings. *expl* is the percentage of the area explored by the robot, $\#M$ is the number of maps that cover at least *expl* area, $|P|$ is the number of partial rooms in such maps. We indicate the average (standard deviation) IoU of our layout prediction method on partially observed rooms.

625 could be retrieved very reliably and their inclusion could cause an overestimate of the overall prediction accuracy returned by the IoU. Hence, we evaluate the IoU only for rooms for which an actual prediction of the layout is made, namely for those partial rooms where $\hat{F}_i^* \neq \{\}$. Overall, we consider for evaluation 482 partial rooms P obtained in 196 grid maps M .

630 The results are shown in Table 2. Overall, considering maps obtained at different stages of exploration altogether, we obtain an average IoU of 0.70, over all the partial rooms for which a layout has been predicted. However, it can be seen how the performance in predicting the layout of partial rooms increases during exploration. We obtain a performance of 0.75 after half of the environment has been observed and of 0.86 when the 90% of the environment
635 has been observed. It is also interesting to point out that the standard deviation of the IoU decreases when the explored area increases.

As discussed in Section 2, alternative methods require a library of environments, consider fully or almost fully observed rooms, or do not predict the geometrical structure of the unknown parts of the environment. So, comparing
640 them with our approach is not immediate nor fair.

Figure 10 shows four examples of layout prediction starting from grid maps

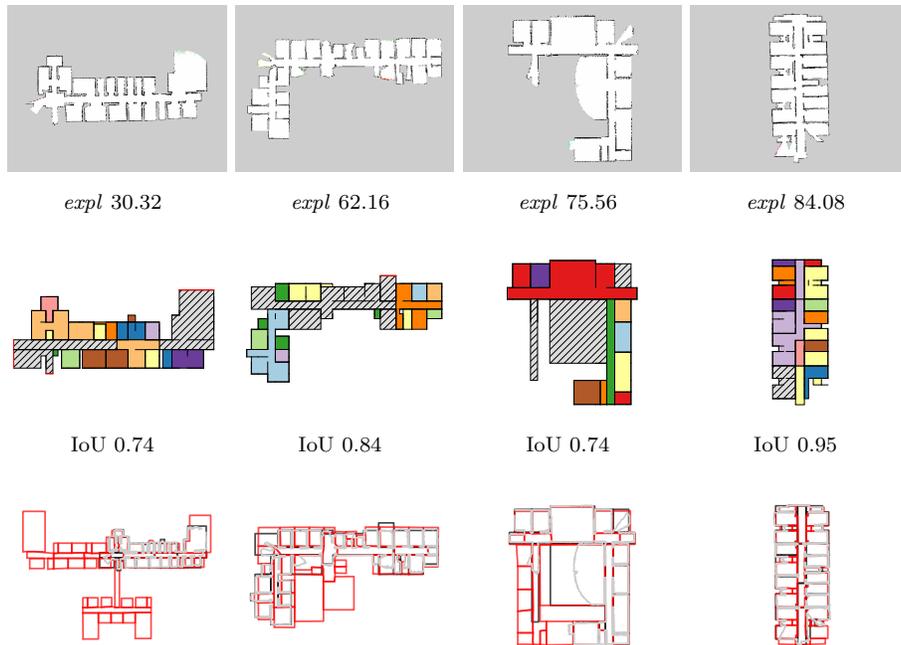


Figure 10: Four reconstructed layouts for different environments. First row: partial grid maps (*expl* is the percentage of explored area wrt the total area of the environment). Second row: reconstructed layouts (with average IoU over the partial rooms). Third row: partial grid maps (gray), reconstructed layouts (black), and ground truth (red).

with partial rooms. The examples are relative to four different environments at different stages of exploration in order to assess the proposed method in different settings.

The first column of Figure 10 shows the case of a very large building of which several rooms have been already observed, and where the map M covers only the 30% of the total area. Despite the fact that our method cannot infer correctly the T-shaped structure of the building from the partial grid map, we are able to correctly identify the open frontiers (in red) that lead to other parts of the building. The average IoU is 0.74.

The second column of Figure 10 shows how our method can infer the shape of several rooms in a halfway-known building. It can be seen that the predicted

shape of partial rooms is consistent wrt their real aspect, despite the fact that
655 not all the walls have been fully observed, as it can be seen by looking at the
rooms that are on the corridor (in orange) of the top-right of the map, even if
the reconstruction of such corridor is under-segmented.

The third column of Figure 10 shows how our method can correctly estimate
the presence of a long corridor in the left part of the building, similar to the
660 long corridor that has been observed in the right part of the building that has
already been explored.

The fourth column of Figure 10 presents an almost fully observed environ-
ment, where the layout of the few partial rooms in the bottom-left part of the
building is correctly predicted using the structural information obtained from
665 the other rooms. This example shows that our method performs well with par-
tial grid maps of complex buildings and copes with gaps in the maps (small
frontiers left behind corners) and (relatively small) inaccuracies, like the fact
that the metric map is slightly distorted.

We now discuss layout prediction for two environments at different stages of
670 exploration. These two examples show what type of knowledge can be inferred
by using our proposed approach during an exploration run. We evaluate the
results obtained when predicting the layout of partially observed rooms using
the IoU metric and the results obtained when reconstructing the layout from
the complete map at the end of exploration using the forward accuracy and
675 backward accuracy metrics of Section 4.1.

The predictions at different exploration stages are independent of each other;
namely, the prediction performed from grid map M_t at time step t is not used to
compute the prediction from M_{t+1} . While exploration progresses, our method
is able to exploit more knowledge about the structure of the environment. This
680 results in an increased accuracy (IoU) of the predicted layout of partially ob-
served rooms. However, the increase of the IoU cannot be strictly monotonic,
because the partial rooms whose layout is predicted change at each stage.

Figure 11 presents a first example of the application of our approach to
an environment at different stages of exploration. Note that, as expected, the

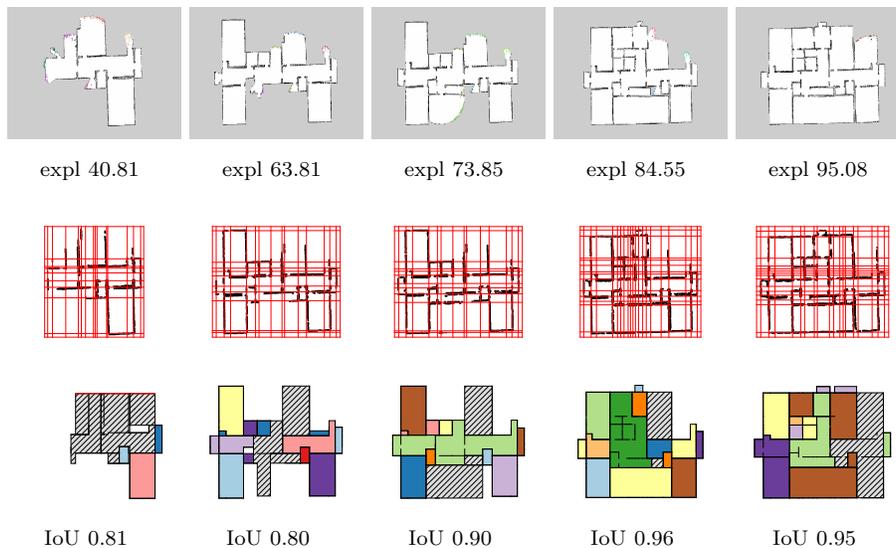


Figure 11: First example of application of our approach to increasingly complete grid maps of an environment.

685 accuracy of the predicted layout improves with the completeness of the grid map and, consequently, with the number of structural features discovered in the environment. The predicted layout of partial rooms is accurate from the second stage shown in the figure, namely after both the upper and lower walls that constitute the border of the image are observed. The correctness of the reconstructed layout of fully observed rooms improves as exploration progresses. 690 During the early stages of exploration, walls inside the environment are correctly reconstructed. However, the segmentation of the space into rooms is often incorrect, resulting in under-segmentation. This is particularly evident in the third and fourth stages shown in Figure 11, when exploration is between 70% and 85%. In both cases, the central corridor (in green) is considered as a part of a larger room. However, when exploration is complete, the full layout \mathcal{L} is correctly retrieved with $A_{FC} = 86.36$ and $A_{BC} = 88.74$, as shown in Figure 12.

Figure 13 shows the second example. Our method identifies correctly open frontiers that lead to other portions of the environment at early stages of explo-

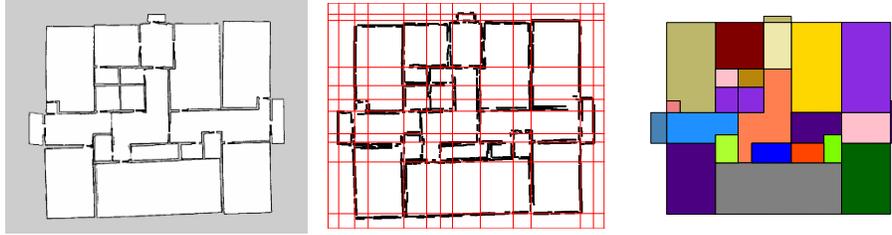


Figure 12: Reconstructed layout of the complete map of Figure 11.

700 ration (e.g., the central corridor in the first three stages shown in the figure). After the largest part of the environment has been observed (fourth and fifth stages), our method is able to provide an accurate prediction of the layout. In particular, in the last stage, our method is able to predict the layout of the last room at the bottom of the right corridor by using the information obtained on
 705 the left corridor of the building. While exploration progresses, the accuracy of the layout reconstruction of fully observed rooms improves as well and, at the end of exploration, we obtain $A_{FC} = 89.6$ and $A_{BC} = 86.5$ (Figure 14).

Finally, in Figure 15 it can be seen that our method is able to correctly identify walls even when a small portion of the environment has been explored.
 710 More precisely, a good prediction can be obtained when the bounding walls of the environment or one of the corridors are observed. Using such information, our method is able to provide meaningful knowledge about the structure of the environment. Open frontiers, in red, are detected at the end of the two corridors that led to the rest of the building.

715 4.5. Computing time and application to an online exploratino process

Our proposed method retrieves a layout \mathcal{L} (both from complete and from incomplete maps) in less than 10s on a commercial laptop, meaning that an updated version of \mathcal{L} is available to a robot every 10s, at most. This computing time is compatible with the online use of our method in several applications,
 720 where a mobile robot can use \mathcal{L} for decision making.

In this section, we provide an example of such an application, namely the

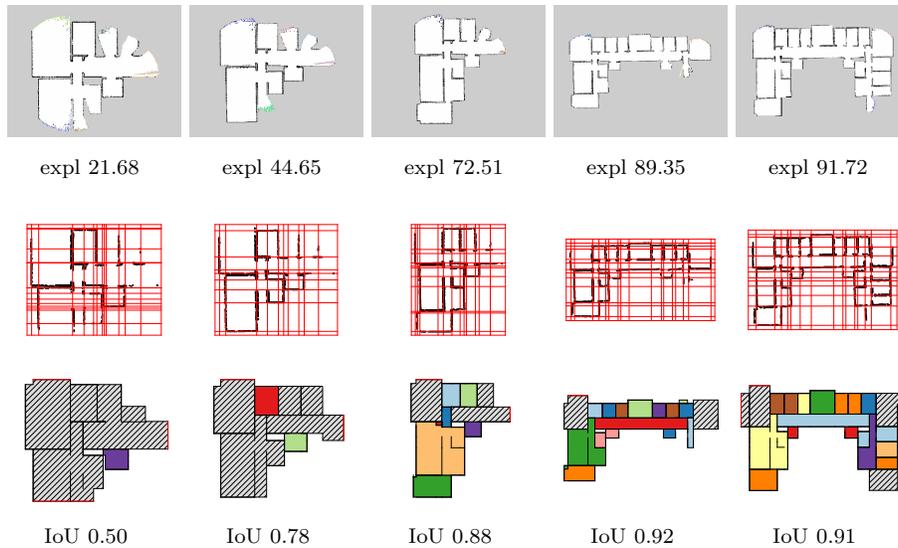


Figure 13: Second example of application of our approach to increasingly complete grid maps of an environment.

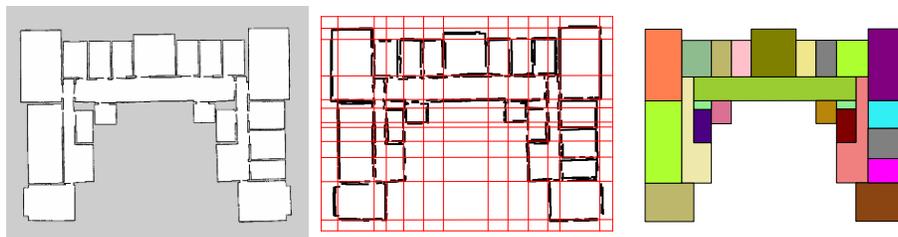


Figure 14: Reconstructed layout of the complete map of Figure 13.

725 online use of our method for the exploration of initially unknown environments for map building. During this process, a robot iteratively selects the next best location to visit in order to quickly cover the entirety of an environment, according to an exploration strategy. A fully detailed account of what is reported here is available in [8].

The exploration process works with the robot that iteratively performs the following steps:

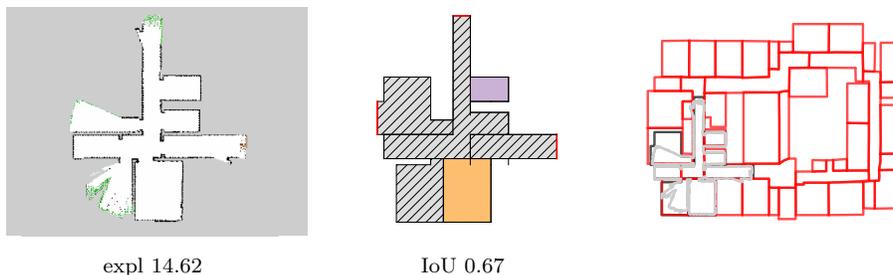


Figure 15: Retrieved layout at an early stage of exploration.

- 730 (i) it extracts from the map M a list of frontiers and, for each frontier, it selects a candidate location p as the middle cell of the frontier;
- (ii) it evaluates the candidate locations $\{p\}$ using an evaluation function $f()$;
- (iii) it selects the next best location p^* as $p^* = \arg \max_p f(p)$;
- (iv) it plans and follows a path towards p^* , integrating the perceptions acquired along the way into the map M ; and
- 735 (v) once it reaches p^* , it restarts from (i).

In this process, we use the layout \mathcal{L} in order to inform the evaluation of candidate locations during step (ii). In particular, \mathcal{L} is used to estimate the amount of new area that is visible from a candidate location p , which is one of the components of $f()$. (Please see [8] for full details.) What is important here is that step 740 (ii) happens at scales of dozens of seconds (considering the time spent by the robot in traveling to a new location a large environment). If no updated \mathcal{L} is available when executing step (ii), the robot waits before proceeding to step (iii). We empirically observed that this never happened in our experiments, indicating that obtaining an updated \mathcal{L} is not a bottleneck for the robot during 745 exploration. In what follows, we present some results in order to evaluate the online use of our method in this exploration context.

We implement our exploration framework in ROS, using the ROS navigation stack. Explorations are performed in 10 large-scale buildings (from 1000 m² to

3500 m²) simulated in Stage (the same environments of Section 4.4, as that of
 750 Figure 13), using a simulated robot equipped with a laser range scanner with a
 field of view of 180° and a range of 6 m and traveling with a speed of 0.8 m/s.
 Our method is embedded into a dedicated ROS node. The ROS node receives
 the latest metric map M from the SLAM algorithm (in this case the ROS imple-
 mentation of GMapping) and a list of frontiers computed from M by an external
 755 node. After computing \mathcal{L} , the node publishes it on a dedicated topic. Note that
 outsourcing the computation of the frontiers (which is one of the differences be-
 tween our implementation and that of [10] and [11]) allows the introduction of
 parallelization within our method, as the process of identifying the frontiers in-
 side a grid map can be time consuming [40]. While the computation of frontiers
 760 is not a core part of our method, the availability of a list of frontiers is required
 to compute \mathcal{L} (specifically, to predict \mathcal{L}_P , as discussed in Section 3.2). Frontier
 computation amounts on average to about 40% of total computing time, with
 a maximum around 60%.

In each of the environments, we perform 10 runs, for a total of 100 runs, in
 765 which the robot fully explores the environments. The total area of the environ-
 ments and the time required to fully explore them (averaged over 10 runs) are
 reported in Table 3. The complete exploration system, including our module for
 retrieving \mathcal{L} , the SLAM module, and the ROS navigation stack (as well as the
 robot simulation), is executed on a commercial laptop, without any dedicated
 770 hardware. As said, in none of the runs, the robot has to wait for the computa-
 tion of \mathcal{L} to end in step (ii). Thus, we have empirically shown that our method
 can be used for supporting the online decision-making of an exploring robot.

In general, the time required to compute \mathcal{L} is proportional to the number
 of rooms in each map. However, as the rooms are considered sequentially,
 775 computing the layout of a room is independent from computing the layout of
 other rooms. The mere prediction of the layout of a single room (i.e., the body
 of the for cycle in Algorithm 2) for the environments considered in Section 4.4
 takes on average 0.028 s. Note that although we could parallelize the retrieval
 of the layout for different rooms, we do not exploit this opportunity in our

Environment	Area	Time
#1	1420 m ²	1715 s
#2	1000 m ²	1636 s
#3	3410 m ²	4187 s
#4	1270 m ²	2482 s
#5	1740 m ²	2477 s
#6	2820 m ²	2842 s
#7	3180 m ²	4265 s
#8	2150 m ²	3537 s
#9	1950 m ²	4275 s
#10	1800 m ²	3508 s

Table 3: Area and average time required by a robot to perform a full exploration of environments where our method is used to retrieve the layout \mathcal{L} that informs the selection of the next location to reach.

780 experiments.

4.6. Evaluation with real-world maps

In order to assess the ability of our proposed method to reconstruct and predict the layout starting from metric maps acquired by real robots, which usually feature the presence of furniture, clutter, and non-structural elements, we
785 present two examples of layout reconstruction and prediction performed starting from such metric maps. In these examples, the layout of the environment is retrieved without applying significant changes to the proposed method used for the more “regular” metric maps obtained from simulations and described in the previous sections. The only change, as we discuss in more detail in the
790 following section, regards the values of two parameters.

Metric maps obtained in cluttered environments present a large number of frontiers (of different sizes) that are due to unexplored parts of the environment that are behind some obstacles. For this reason, as described in Section 3.2, our

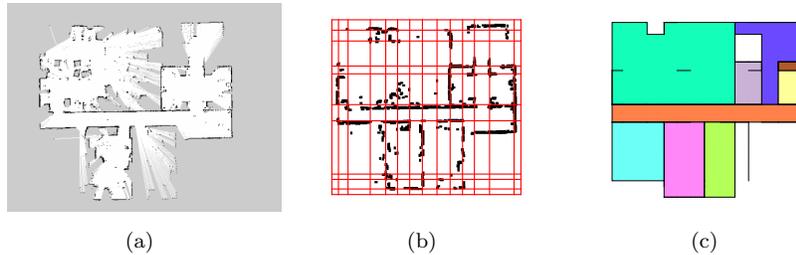


Figure 16: Retrieved layout of a cluttered map obtained by a real robot (from [41]).

method considers all the rooms in which the frontiers lie as partially observed
 795 and thus their layout is predicted. Our method, consequently, tries to remove
 clutter and to fill gaps to obtain a clean and abstract representation of each
 room, for example approximating as rectangles the rooms with small columns
 close to the walls. Despite this fact, and the fact that metric maps obtained
 in real-world environments are significantly different from those obtained in
 800 simulation, our method is able to successfully reconstruct and predict their
 layout.

Figure 16 presents the first example, relative to a house environment from
 [41]. The map of Figure 16a presents clutter in all of the rooms, with only the
 main corridor in the middle being completely observed and mapped by the robot.
 805 The big room in the upper-left part of the map has been almost fully observed
 by the robot, but presents several unseen parts due to the clutter. However,
 the representative lines obtained from the observed portion of the environment
 (Figure 16b) provide a segmentation of the map into a few meaningful faces. The
 reconstructed layout, in Figure 16c, provides a reasonable guess of the structure
 810 of the environment, as shown by the fact that the room in the upper-left part of
 the map is correctly predicted to be a big almost-rectangular room and that the
 layout of the three rooms connected to the corridor at the bottom of the map
 (in light-blue, pink, and green, respectively) are successfully predicted. Note
 that all of the rooms of this example, except the central corridor, are classified
 815 as partial rooms due to the presence of frontiers. However, for better clarity,

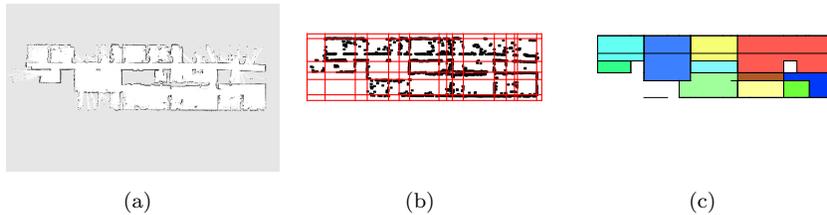


Figure 17: Retrieved layout of a cluttered map obtained by a real robot (from [42]).

we adopt here a color scheme different of the one used for the other examples of Section 4.4, where partially observed rooms are denoted with a dashed gray pattern.

In the second example, we applied our method to one of the publicly available maps of [42] (Figure 17). Also in this case, the map of Figure 17a presents clutter
 820 in most of the rooms. Moreover, some rooms connected to the upper part of the corridor are only partially observed, as the robot has not entered in them while mapping. In Figure 17b, it can be seen how our method is able to provide a valid segmentation of the environment, which is then used in Figure 17c to
 825 reconstruct and predict the layout of the environment in a meaningful way. In this example, due to the presence of several partially observed rooms, our method tends to under-segment the rooms, in particular those connected to the upper corridor.

This fact suggests that, despite segmentation of the environment using few
 830 representative lines could effectively predict the layout of the environment, the clustering method used for grouping faces into rooms could be adapted in order to cope better with cluttered settings, as in the case of maps obtained with real robots. For example, it would be interesting to execute the proposed method online by filtering out clutter using a method similar to that of [43].

835 4.7. Discussion

The examples presented above show that our proposed method is able to reconstruct and predict the layout of environments from metric maps in several

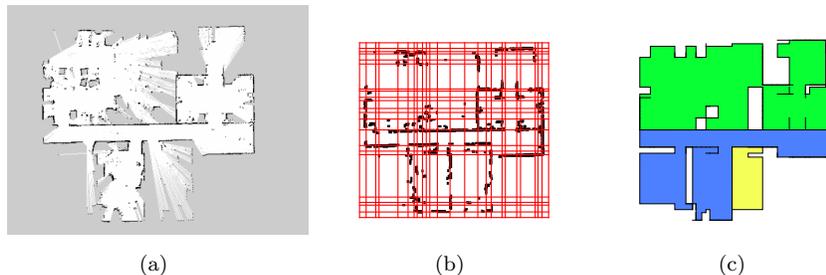


Figure 18: Reconstructed layout of the map of Figure 16, where more representative lines are used.

different settings. At the core of the method there is the fact that it segments the environment using relatively *few* representative lines which successfully capture the underlying structure of buildings and their regularities. Indeed, these representative lines are used to retrieve the direction of the main walls, ignoring clutter and small details that can be found in metric maps (see, for a different approach, [18]).

For this reason, our method can be easily adapted without changes to different settings, provided that representative lines are determined according to the main walls of the environment. From our experience, the only modifications required in order to adapt our method to different input metric maps are relative to the identification of the line segments S , using the probabilistic Hough line transform (Figure 2c), and to the clustering of collinear line segments in sets $W_{j,k}$, which are later used for computing the representative lines and the faces. In particular, we observed that the outcome of our method is mainly influenced by two parameters $\theta = (\text{minLinPoints}, \text{wall})$, namely the minimum number of points that could be considered as a line and the threshold for merging collinear line segments. In general, we set $\theta = (7, 10)$, but we change them for input metric maps obtained by real robots. Specifically, we use $\theta = (40, 20)$ for the map of Figure 16 and $\theta = (60, 12)$ for the map of Figure 17. Consider, for example, Figure 18, which shows the layout reconstruction of the same environment of Figure 16 when using $\theta = (30, 10)$, which results in a larger number

of representative lines detected within the map and, consequently, in a larger
860 number of faces. Comparing Figure 16b to Figure 18b and Figure 16c to Figure
18c, a larger number of representative lines results into a less abstract and less
“clean” representation of the environment. The rooms identified in Figure 18c
represent not only the main structure of the rooms, but also small rooms due to
clutter. With more suitable values $\theta = (40, 20)$ our proposed method, as shown
865 in Figure 16c, produces a cleaner and more abstract representation of rooms’
shapes, representing each room with a polygon that is retrieved from the main
walls and better capturing the underlying structure of the entire building. As a
consequence, although several parameters are used in the steps composing our
method, only the two parameters θ should be set to identify, within the input
870 metric map M , only those line segments S that lie along the main walls of the
building.

In all the examples discussed above, experimental evaluation has been per-
formed considering as metric maps M grid maps whose cells can assume (pos-
sibly after thresholding the maps built by GMapping) only three values: free,
875 obstacle, and unknown. This allows to apply our method to input metric maps
coming from different sources, like evacuation maps, blueprints, and partial
maps built by real robots (see Sections 4.3 and 4.6), as we consider as candidate
cells for wall identification only those cells labeled as obstacle. However, more
informative map representations based on fine-grained probability distributions
880 on the occupancy of cells can be adopted. These maps, as those based on the
Dempster-Shafer theory [44] and the NDT maps [45], represent the degree of
uncertainty about the occupancy of each portion of the environment and have
been proven to be particular useful when considering long-term and dynamic
settings, in which distinguishing between stable and static map elements (e.g.,
885 walls, which typically correspond to highly certain occupancy) and dynamic and
transient ones (e.g., moving obstacles, which typically correspond to uncertain
occupancy) is particularly important. The integration of such knowledge into
our method could be beneficial and information about the occupancy probability
of cells might be useful in order to retrieve good candidates for the representative

890 lines of the walls in the environment.

Our method is based on 2D metric maps, typically grid maps obtained with 2D laser range scanners, that, as we discussed previously, are simpler and less rich representations than the 3D point clouds used for example in [5, 21]. 3D maps provide more knowledge about the environment (e.g., they allow to retrieve the walls of the environment from the detection of the ceilings or from the identification of the doors as gaps on planar surfaces) at the expenses of requiring more complex sensors (e.g., Velodynes or RGBD cameras) and more complex SLAM processing, implying larger computing efforts. Our approach, requiring only 2D metric maps, can be applied to input maps obtained by cheap and simple robots, like domestic robots (e.g., vacuum cleaning and socially assistive robots) and research platforms (e.g, TurtleBots). The layout returned by our method can be used for several tasks, starting from identifying rooms within the map and regularizing inaccurate portions of the maps. For instance, a map can have some “gaps” due to the fact that the robot has observed and mapped only portions of some rooms while passing (without entering) in front of their open doors. This lack of knowledge constitutes a limitation to the robot’s operations, because it cannot plan to perform any task in the unmapped areas. Our method could be used to smooth such a limitation by predicting portions of the map that are not fully observed at mapping time. An example of a possible online use of our method is provided in Section 4.5 and detailed in [8]. Moreover, an adaptation of our method to predict the layout of completely unexplored rooms that are behind closed doors is presented in [46]. Finally, in [47] our method is embedded in a framework for detecting robust features in indoor maps in order to evaluate map quality.

915 While the current performance of our method allows its use in some online applications of ground robots, fast-moving robots (e.g., UAVs) may require the availability of a fresh \mathcal{L} at higher frequencies. In this case, our method can be further improved as follows. Some steps, like the computation of line segments from walls and the computation of frontiers, that extract rather stable features about the environment, can be performed at low frequency or on-demand upon

major changes in the metric map M . Other steps, like the prediction of the layout of rooms, can be performed as a separate process at higher frequency and only for rooms for which the metric map M has significantly changed. Such high-frequency updates can be obtained up to 5 Hz, according to results
925 reported at the end of Section 4.5. However, we leave such improvements as future work.

5. Conclusions

In this paper, we have presented a method for retrieving the layout of an indoor environment given its 2D metric map, like the one that could be obtained
930 from laser range scanners onboard of autonomous mobile robots. Our method reconstructs the layout of those rooms which have been completely observed by the robot and predicts a possible layout of rooms that have been only partially observed, exploiting structural features extracted from the observed parts of the environment.

935 Experimental results show that the proposed method performs well and is able to cope with complete and partial metric maps of large-scale buildings, not only when the input maps are grid maps, but also with blueprints and evacuation maps. Experiments performed using maps at different degrees of completion show that our method is able to predict a possible layout, even
940 when only relatively small portions of the environment have been covered by the robot.

Future work, in addition to what has been mentioned along the paper, includes the combination of our method with room segmentation approaches to investigate if better performance can be obtained by looking both at the global
945 structural features and at the local features of the buildings. Our method could be extended to input maps that can be transformed in 2D maps composed of line segments (e.g., 3D point clouds). The use of sketch maps [37, 38] as input is also a promising further development. Improvements of the proposed method include, for example, enlarging the family \mathcal{F} of candidate sets of faces,

950 by using a heuristic to efficiently search it, and by exploiting regularities identified in other environments in the utility function $\Phi()$. It would be interesting to integrate our method with prior knowledge of the floor plans and assess its performance in partial maps with increasingly larger levels of noise and clutter. Moreover, the proposed method could be improved by detecting and explicitly
955 exploiting symmetries between different parts of the building, for example using the methods from [28, 48]. Finally, we look for other applications of the method proposed in this paper, beyond those relative to exploration [8, 9].

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