LIDAR Signature based Node Detection and Classification in graph topological maps for indoor navigation

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Abstract. Topological map extraction is essential as an abstraction of the environment in many robotic navigation-related tasks. Although many algorithms have been proposed, an efficient and accurate modelling of a topological map is still challenging, especially in complex and symmetrical real environments. In order to detect relevant changes of trajectory or a robotic platform, we propose a feature extraction model based on LIDAR scans to classify the nodes of indoor structures. As a first approach we support the experiments in a preloaded metric map, which has been used as reference for locating the nodes. Experiments are conducted in a real scenario with a differential robot. Results demonstrate that our model is able to establish the graph automatically and with precision, and that it can be used as an efficient tool for patrolling.

Keywords: Assistive Robot · Topological Map · Node Classification.

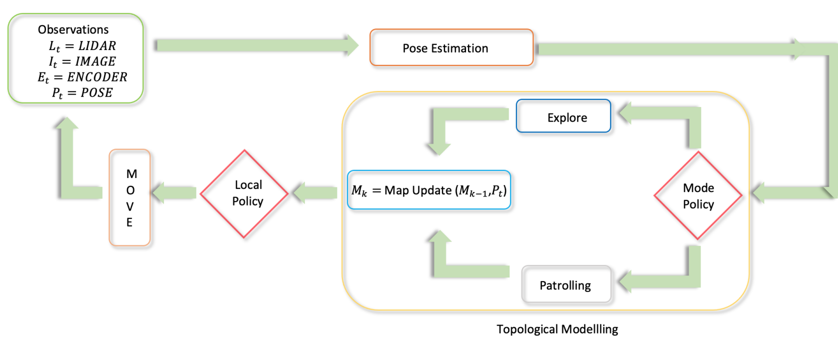
1 Introduction

In many robotic navigation-related tasks, abstracting the real environment where mobile robots carry out some missions can be of a great benefit. In particular extracting a simple topological graph-like representation from a more complex detailed metric map is often required for path-planning and navigation. A topological graph, as defined by Simhon and Dudek [1], is a graph representation of an environment in which the important elements are defined along with the transitions among them. In complex real indoor environments, such as hospitals, residences and office buildings, the structure presents high level of symmetry and usually consists of many corridors in which rooms are distributed on both sides.

The dynamic nature of these environments, which are generally frequented by many people, means that the topological map can undergo continuous changes. Thus, for example, the opening or closing of doors adaptively forces the topological map to create new paths and remove others, respectively. The dynamic and complex nature of these scenarios is a major challenge.

In this paper, we focus on the extraction of nodes in symmetrical indoor environments based on distributions of numerous corridors. In our approach, nodes represent relevant changes of direction, such as an end of aisle or a bifurcation, where several outlets are possible. As depth information for node classification, we rely on LIDAR scanning. Fig.1 shows a block diagram of the proposed approach. The complete process is performed automatically using the metric map as input and consists of three main modules: 1) pose estimation, which uses a particle filter to track the pose of a robot against a known map; 2) a classification of the scene to detect and classify the nodes (topological modelling); and 3) a local policy sub-system to determine the sequence of movements. The system can be in two operating modes: exploration or patrol. In the first one, the platform creates the topological map of the scenario. On the other hand, when the agent is on patrol performs a routine navigation based on the topological map already created. It is in patrol mode where the maintenance of the topological map is performed, since the robot is able to discover changes when detecting the presence of new nodes or the disappearance of previous ones.

Taking into account the pose estimations of the particle filter, the system positions the detected nodes in route on the pre-loaded metric map. The model has been evaluated by means of a case study using an area of a university building.



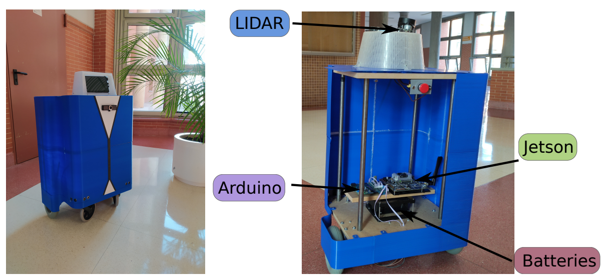
(a)

Fig. 1. Overview of the proposed system.

In summary, the main contributions of this work are as follows:

– We introduce a novel approach for topological mapping, adapted to symmetrical spaces based on corridor layouts, where nodes identify relevant changes

of trajectory. Although similar approaches can be found in [2, 3] based on classification of the positions of the robot (rooms, corridors, doorways, hallways, ...), we focus on the detection of corridor junctions through an efficient SVM-based approach.
- We use the semantic information from the objects found by means of a trained YOLO-v3 [4] based detector to automatically locate the nodes in the map.
- We present a thorough experimental evaluation embedding the proposed approach in our own low-cost assistive robotic platform (see Fig.2). It is a differential wheeled robot, equipped with two motors and their corresponding encoders, which are all controlled with an open-source Arduino board. The sensing part is composed of an Intel RealSense D435 camera and a LIDAR. An on-board laptop with a Nvidia board Quadro RTX 5000 and/or a Nvidia Jetson TX2 board are provided for intensive computation.



(a) (b)

Fig. 2. LOLA robotic platform. (a) Frontal picture. (b) Internal structure.

This paper is organized as follows. We start by an overview of related work in Section 2. In Section 3, we introduce the approach for the classification of nodes, while the topological modelling strategy is described in Section 4. Results are presented in Section 5. Finally, Section 6 concludes the paper and outlines future research.

2 Related Work

Navigation systems are based on metric, topological, and semantic maps, depending on the level of abstraction of the environment representation [5]. In the literature, a large variety of solutions to this problem is available. One intuitive way of formulating SLAM is to use a graph whose nodes correspond to the poses of the robot at different points in time and whose edges represent constraints between the poses.

Regarding topological navigation, since the first developments, the global conception of the system has attracted the interest of several authors. Surveys of models for indoor navigation are provided by [6–8] among others. Comparison of various graph-based models is provided in a very clear way in Kielar et al. in [9]. The main contribution of this work was the development of a low-cost process for building navigation graphs based only on geometry nodes. Topomap [10] is a framework which simplifies the navigation task by providing a map to the robot which is tailored for path planning use. Each vertex corresponds to a certain partially enclosed area within the environment (e.g. a room) which is connected to neighboring vertices. In our case, vertices represents points where a movement decision must be taken.

Enriched information can be provided by different sensors. A robot navigational method was presented in [11] based on an Extremum Seeking algorithm using Wireless Sensor Network topology maps. On the other hand, each node in the graph is associated with a panoramic image in [12]. The problem of image-goal navigation involves navigating in a novel previously unseen environment. For this task, a neural topological map was constructed. However, there is no additional information in our low-cost platform than the captured by the RGB-D camera or LIDAR.

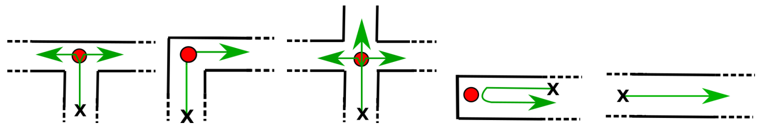
A more similar to ours classification of space was given in [13] what they call types of corridors. They performed classification from different positions while the robot was moving and this allows to avoid wrong classifications. A Bayesian classifier was used to obtain the corridor types.

3 Classification of nodes in the topological map

A topological map is a graph-based representation of the environment. Each node corresponds to a characteristic feature or zone of the environment. In our approach, we consider as points of interest those ones that imply a change of trajectory. Regarding to this criterion, common corridor structures can be classified into four node categories in our map:

– End node: there is no outlet at the front, neither from the left nor from the right of the corridor. The agent cannot follow the path.
– Node ‘T’: there are two outlets for the agent since the corridor presents two lateral bifurcations. This node type is also called Node ‘Y’ in other works as [13].
– Node ‘L’: the path presents an marked change of direction. We have considered in this category changes of direction involving angles greater than 40°, regardless of whether the turn is from the left or from the right.
– Cross node: the corridor presents three or more outlets (two laterals: left and right, and another frontal one).

In addition, we introduce the category of a complementary type called No Node. It is used to incorporate additional context into the exploration, and refers to the zones of transition between the above mentioned categories, while the robot is moving along the corridors. Figure 3 represents the different categories considered in this work. Thus, for each type of node, we represent the location of the robot (X) and the possible trajectories depicted in green.



(a) (b) (c) (d) (e)

Fig. 3. Types of nodes considered in a building with dense distribution of corridors. (a) Node 'T'. (b) Node 'L'. (c) Cross node. (d) End node. (e) No node.

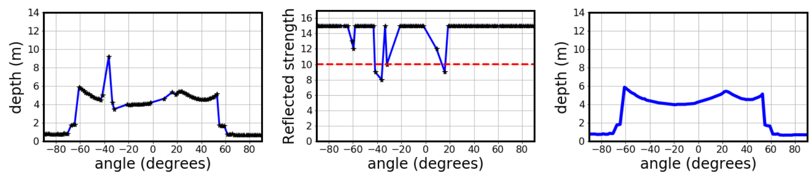
3.1 Extraction of features

Different techniques can be utilized to obtain depth information. In this work we have used a laser range scanner, more specifically, the RPLIDAR A1 of the manufacturer Slamtec [14]. RPLIDAR is a low cost 2D LIDAR sensor suitable for indoor robotic applications. It provides 5.5hz/10hz rotating frequency within a 12-meter range distance. Each raw measurement is a tuple with the following format: quality, angle, distance. The quality indicates the reflected laser pulse strength, the measurement heading angle is given in degrees and object distances are related to the sensor's rotation center.

Even when the LIDAR sensor has one degree angular resolution, the angular resolution of RPLIDAR is not necessarily regular, that is, the spacing between two points is not necessarily the same. This is the reason why we need to fit a linear interpolation method to fill missing values. However, not all real depth curves are ideal. Due to sensor noises, irregular surfaces and obstacles, the capture contains fake information. Reflected sunlight from windows and directions of great depth provoke, in general, outliers of low strength. To overcome these disturbances, we propose a filtering process in which measurements of low reflected strength are discarded.

As an example, Fig. 4 shows an scan laser, where 4(a) represents the raw samples (black markers) and the quality is shown in 4(b). The signature (4(c)) is obtained after having set a quality threshold of strength equal to 10. Note that we limit the angular range of the laser scans from $-90°$ to $90°$ because depending on the mobile platform structure the back side may intercept the beam.

The features play an important role in the classification algorithms to identify node types. We have established as parameter the number of bins N_b, which is related to the number of intervals into which we divide the angular range of measurements. Thus, the depth vector or LIDAR signature can be defined as $\mathbf{d} = (d_1, d_2, \ldots, d_{N_b})^T$. Two strategies have been considered to define the value



(a) (b) (c)

Fig. 4. Process of extraction of LIDAR signature. (a) Raw LIDAR scan. (b) Laser pulse strength. (c) Filtered signature.

of each feature d_i: 1) the normalized value of LIDAR signature at the center of the corresponding bin considering the maximum range distance of LIDAR (12 meters); and 2) a binary feature that can be interpreted as a prediction of whether there is explorable area in the particular direction or not.

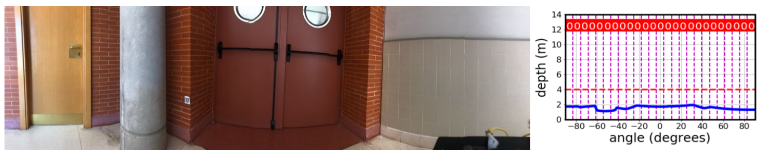
Fig. 5 shows some examples of the proposed LIDAR signature for different nodes having fixed $N_b = 25$. For each node we can observe the panoramic image in the range of interest, where the green arrows indicate the possible outlets, and the LIDAR signatures. Binary sequences have been obtained by setting a depth threshold $T_h = 4$ meters, which is represented by a dotted line. The green and red boxes show explorable (free space) and non-explorable directions, respectively.

It is important to note that different patterns can be captured in the same type of node depending on the input access. Thus, the patterns are quite different in Figs. 5(b) and 5(c) even though they correspond to the same node, but with different robot poses. LIDAR signatures are highly dependent on the robot-corridor orientation. In this work, a robot controller ensures that during the reposition phase (such as the turning and obstacle avoiding phase), the classification process is suspended to prevent wrong observations. In this way, classification is only activated when the robot moves along the central line between the side walls.

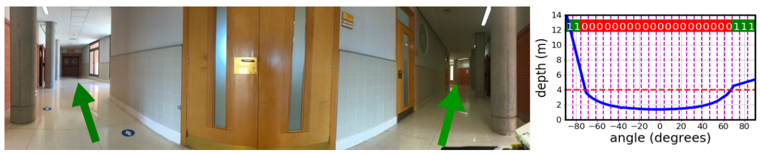
The LIDAR signature feeds the input of our classifier whose output determines the node type. Because the efficiency of Support Vector Machines (SVMs) [15]-based approaches for classification has been widely tested in the scientific community, we have used this technique as a base of our classification module, also because of its generalization properties.

4 Topological modelling

Taking into account the pose estimations of the particle filter when the robot is moving in the indoor environment, the system is able to positioning the detected nodes on a pre-loaded metric map. Figure 6(a) represents an example of detected nodes where our four categories, including No-Node, appear over an ocuppancy map. Here, white area denotes free locations, whereas black means occupied positions and grey means inaccessible. Each detected node is depicted



(a)



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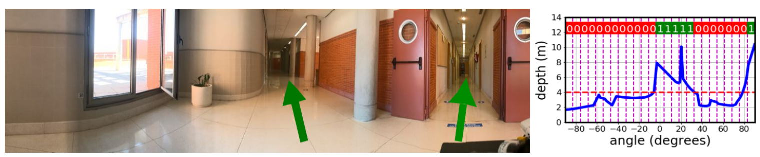


(c)

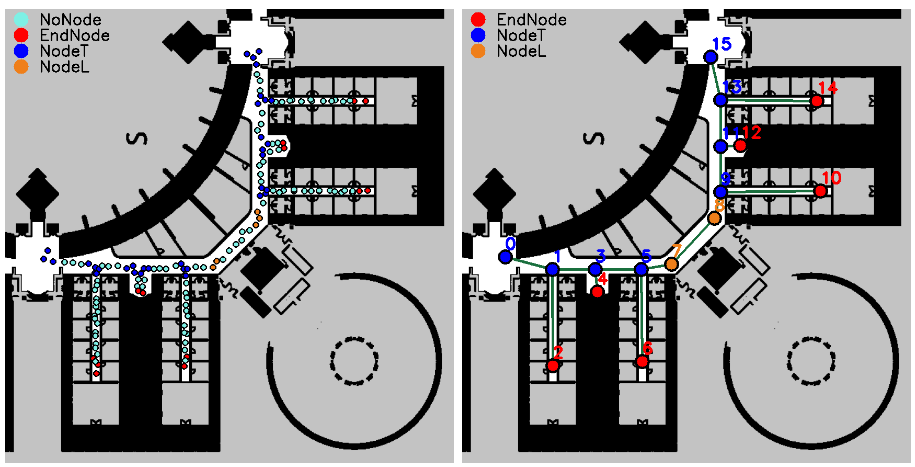
(d)

(e)

Fig. 5. Examples of node signatures. (a) End node. (b) Node T (example 1). (c) Node T (example 2). (d) Cross-node. (e) No node.

by a different color depending on its category and transitions between relevant zones are classified as no-nodes.

When the mobile robot moves, it receives multiple observations of the same node and progressively obtains the classification. The nodes of the topological map (see Fig.6(b)) are computed in real-time as the centroids of the resulting clusters using an agglomerative clustering algorithm with some restrictions. Thus, we set the maximum distance between nodes of the same type withing a cluster to a value $d_{max} = 4$ m and set the minimum number of points per cluster as $N_{min} = 2$. The generated map is represented using a graph, which is denoted by G_t at time t. Two nodes n_i and n_j are connected by an edge $E_{i,j}$. In order to build the graph we take into account the fact that all accesses in each node must be connected to other nodes. The existence of an end-node implies the end of an exploring path. From these graphs, we can establish a patrolling system in which nodes constitute the list of way-points to cover.



(a) (b)

Fig. 6. Extraction of topological modelling. (a) Map of identification and localization of node clouds. (b) Topological map representation where each node represents a keypoint and the links connect adjacent nodes.

Pose subsystem (see Fig.1) estimates the location of nodes on the pre-loaded metric map. It is based on a particle filter that uses as input information in each iteration the previous estimated pose, the odometry and the image captured by the RGB-D camera. Multiple object detection allows for a visual interpretation of the scene in the task of estimating the robot pose. For this purpose, we have implemented an object detector based on the YOLO-v3 [4] network, with categories of objects typically found in indoor environments. Specifically, we ran a fine-tuning process retraining YOLO to be adapted in the new domain of our own dataset, which includes the following ten categories: window, door, elevator, fire extinguisher, plant, bench, firehose, lightbox, column and toilet.

5 Results

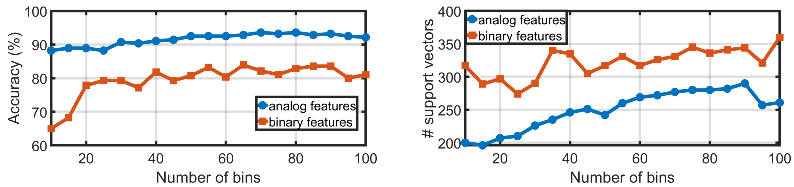
In this work we collected our own dataset to evaluate the performance of the proposed node classification framework. Specifically, we have worked in the building of the Polytechnic School of the University of Alcalá, which is distributed in four floors of approximately 10,000 m^2. The map shown in Fig. 6 corresponds to one of the four similar areas of a floor. The dataset has been captured in this building and is composed of a training set and a test set, where the captures of both sets correspond to different areas. The signatures in this dataset cover a wide range of poses at each type of node. Table 1 presents the description about the dataset.

Table 1. Description of the indoor nodes dataset (number of samples)

	No Node	End Node	Node 'T'	Cross Node	Node 'L'
Training set	137	138	133	44	107
Test set	68	69	67	22	54

One problem that faces the user of an SVM is how to choose a kernel and its specific parameters. Applications of an SVM require a search for the optimum settings for a particular problem. Optimal values of parameters C (regularization parameter) and γ (parameter of influence) were determined in our problem by using a 5-fold cross-validation with the training set. We generated a trained model using these optimal parameters on the full training set. Figure 7(a) shows the overall hit rate of the test set as a function of the number of intervals N_b in which the feature vector is discretized. In addition, as a significant indicator of the computational complexity and overfitting, Fig. 7(b) represents the number of support vectors as a function of N_b in the range [10,100]. In comparison, Figure 7(a) exhibits a great superiority of analog features over binary ones and shows a clear stability of the analog pattern performance for the analyzed range of N_b. The trade-off between accuracy and model complexity led us to set $N_b = 50$ as a good choice with a global accuracy of 92.5%.

Table 2 details the node recognition results obtained on the test set with a total of 280 captures. Results are represented by means of the confusion matrix, using analog patterns with $N_b = 50$. In this case, optimal values of parameters were $\gamma = 1$ and $C = 5$. By inspection, we can observe that there is only seven cases of confusion between categories of specific nodes. Most misclassified examples are due to specific nodes assigned as non nodes. The reason is that the classification system assigns the signature to a specific node class a little before or a little after entering the zone of influence with respect to the labeling



(a) (b)

Fig. 7. Performance of the proposed method. (a) Overall accuracy of the node classification. (b) Number of support vectors

of the sample. Considering this circumstance, we can conclude that the performance of the classifier between specific classes, without considering No-Node class, achieves a good accuracy of 97.5%.

Table 2. Results of node classification (confusion matrix)

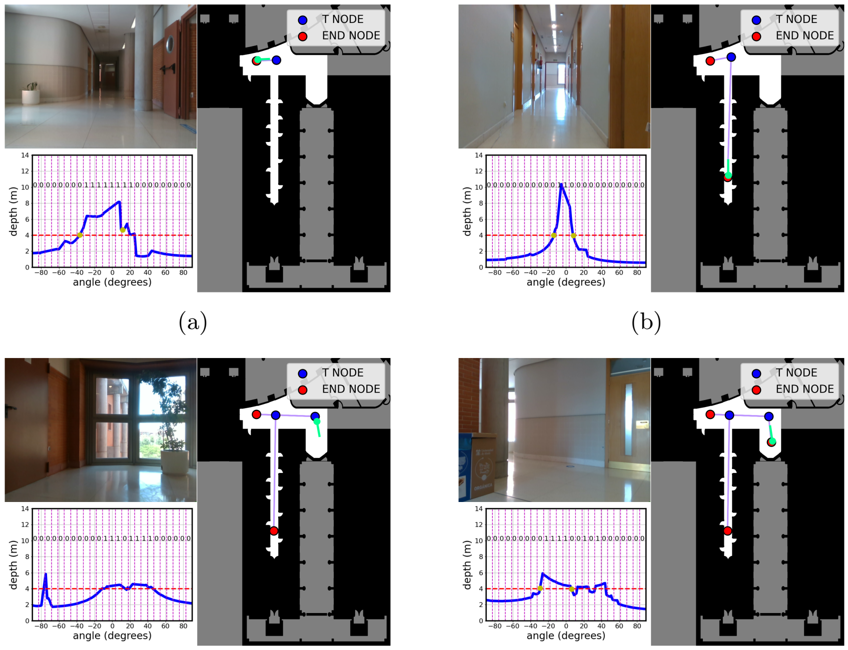
Category	No node	End Node	Node 'T'	Cross node	Node 'L'
No node	61	1	1	0	5
End node	0	66	3	0	0
Node 'T'	2	0	63	1	1
Cross node'	2	0	2	18	0
Node 'L'	3	0	0	0	51

To validate the behaviour of our system, we have generated a demo video [3] that shows the construction of the topological map from the exploration in an area that includes two nodes-T and three End-nodes. In Fig.8 some snapshots of the exploring at different iterations are depicted. The agent completes the exploration after an average of 74 iterations in a total of 4 trials and decides to take the stop action. Note that the algorithm does not represent a new node in the graph until it considers that the robot leaves its zone of influence.

6 Conclusions

An approach for topological modelling in symmetrical indoor buildings has been presented to address a main difficulty: detecting nodes adapted to large spaces based on corridor layouts, where nodes identify changes of trajectory. The presented multiclass node detection solutions is a real-time system that can classify

[3] A video of our experiment is provided: https://universidaddealcala.sharepoint.com/sites/Cadas/Documentos%20compartidos/General/video.mp4



(a) (b) (c) (d)

Fig. 8. Example exploration. Agent observations and LIDAR signatures are shown on the left (upper and bottom, respectively) and the topological map is shown on the right. The green arrow represents the current estimated pose of the robot. (a) (t=21) The model creates the first End-node. (b) (t=44) The model creates the second End-Node. (c) (t=72) The model creates the second node 'T'. (d) (t=77) The model creates the third End-node.

LIDAR signatures into different categories as the robot moves during an exploration process and builds a topological structure of nodes and edge connections.

To evaluate the performance of the proposed method we have conducted a series of experiments using a dataset with 839 annotated LIDAR scans obtained with own robotic platform navigating in a university building. The results of the experiments show that the present method constitutes an efficient system as a first approach and allows the robot to patrol in the given scenario by using the metric map and the extracted topological map. Nodes constitute the list of way-points to cover. For future work, the system should be fully integrated under the Robotic Operating System (ROS). Fusion of RGB-D images and depth information will be investigated for classification of nodes and scenes.

Acknowledgements

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