Some Experiments on a Geometrical Approach to Build Maps in Indoor Environment*

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Abstract. In this paper, we propose some experiments performed to model flat indoor environment using a mobile robot. Our approach uses straight lines as the geometric primitives to describe walls and relevant objects of the scenario under exploration. We use sensor data acquired by a laser range finder. We analyze several cases that could arise in the interpretation of sensor information and its importance for the building task.

1 Introduction

Sensor-based exploration enables a mobile robot to explore an unknown environment and build the map of that environment. That is the reason why techniques for robot map building has been a highly active research area in robotics. Robot map building is based on acquiring a set of data by the sensors and then integrate them into a representation of the environment. The mapping problem is generally regarded as one of the most important problems in the pursuit of building truly autonomous mobile robot [1]. There are basically three types of maps. The Occupancy Grid Maps, first introduced by Moravec and Elfes [2], have been widely used [3], [4], [5]. The occupancy grid maps represent the environment as a two dimensional array of cells, each of which indicates the probability of being occupied. The occupancy grid maps are considerably easy to construct and to maintain even in a large scale environments [6], [7]. Since the intrinsic geometry of a grid corresponds directly to the geometry of the environment, the robot's position can be determined by its position and orientation. On the other hand grid-based approach suffer from their space and time complexity. This is because the resolution of a grid must be fine enough to capture every important detail of the world.

Topological maps are an abstract and compact representation of the environment that captures key places and their connectivity for localisation and navigation [8]. Topological maps represent the environment as a list of significant places, called nodes, connected by arcs. The topological approach in contrast with the grid-based, determines the position of the robot relative to the model based on landmarks. Topological approach often have difficulty determining if two places

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that look alike are the same or not. The advantage for such a representation is its compactness and its potentiality. Examples of topological approaches include the work by Mataric [9] and Gasca-Martínez [10].
Geometric feature based map are build from measurements acquired by a sensor at different instants of time, such as a laser range finder, thus generating a perceptual model defined by line segments. In this paper we propose a geometric map based on line segments as a way to reduce the size of data structure storage. We can then use it in efficient path planning and localization process.
Paper organization is as follows: In Section 2 we pose the problem addressed by this paper and the main elements of our approach. We show in Section 3 the test we have carried out to model on indoor environment and the discussion of the results we have obtained. Paper is finalized by stating our main findings and the work to be done (Section 4).

2 Problem Formulation

The general problem we want to solve is to let a mobile robot explore an unknown environment using its laser range finder and build a map of the environment. Consider an indoor environment as shown in Figure 1, if we place the robot in a position (x, y, θ), we can get the representation of the environment sensed by the robot, based on a feature extraction algorithm. We propose to model such an environment using a geometric map composed of line segments. With this kind of representation, a model of the environment will consist of a sequence of lines. Each line is described by six parameters: its slope-intercept equation in global coordinates and the (x, y) coordinates of the beginning and the end points of the known line segment. In Figure 2, we can see the different processes needed for this approach.

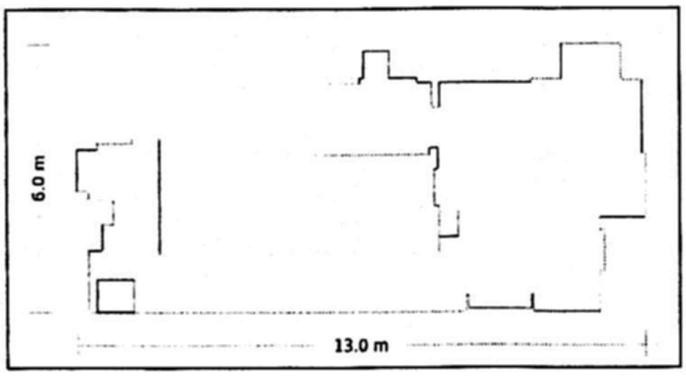


Fig. 1. Geometric map of an environment.

Robot is assumed to be at an initial unknown position (x, y) and with an also unknown orientation θ. Data acquisition is performed by using a laser range

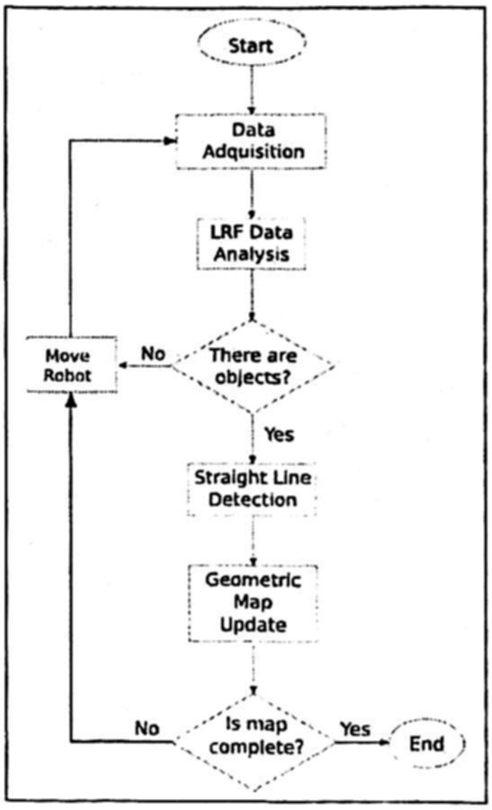


Fig. 2. Information flow through the proposed system.

finder. The acquired laser range finder data is analysed to know if there is relevant objects in the neighborhood of the robot. It is well known that the laser range finder detects objects robustly when they are in a range lower than 10 meters. So we analyze the readings of the laser range finder to detect if there is any object inside this area defined by this range and the current orientation of the robot.

If the robot does not detect any interesting object to start building a map, it changes its configuration to inspect another region of its surrounding environment. Firstly, our strategy is to cover all possible orientations of the robot in its current position. If no object is detected when this operation has been completed, the robot moves forward in the last orientation that has been inspected. Alternatively , we could use free space criteria to decide in which direction the robot has to move forward. This motion is executed until a given time interval is elapsed or until an object comes into the region of the robot, whatever occurs first. If no object has been detected at the end of the forward motion, the motion command is re-issued. Rotation of the robot is only executed in the initialization step, this helps the robot to find near walls not detected in their current orientation.

When the robot detect relevant objects, a straight line detection module tries to identify the walls in the environment under exploration. To do so, we detect the sensor data clusters originated by all the walls in the detection range of the

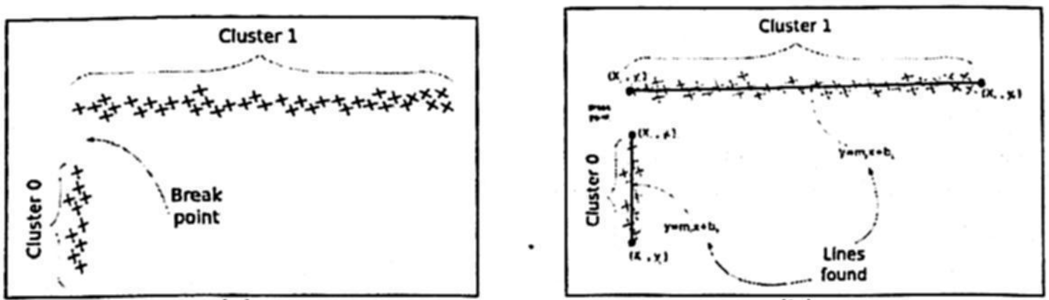
robot. They are then analyzed to fit a straight line model in global coordinates to represent the wall in the map representation.
A geometric map update module incorporates new line models in the current map. The information fusion step considers the motion of the robot in the global coordinate system and it tries to refine the wall description by analyzing line overlapping, parameter similarity, etc.

2.1 Clusters Detection

The clustering process refer to the process of classifying data by groups based on the calculation of a minimum distance that must exist between two consecutive points to consider that they must belong to different clusters. In this work we use an adaptive clustering method proposed by Borges *et al.* [11].
The clustering process is a very important step because we detect the number of groups without break points (see Figure 3(a)), based on a threshold distance parameter, which allows us to determine the different lines accurately.

2.2 Wall Modelling

Once we have all the cluster from the data, we use the *Iterative End Point Fit (IEPF)* algorithm [12] in order to calculate the existing lines associated to the walls of the environment. This step let us to compute the line model only using points that actually belong to a single wall. As a result, we obtain the six parameters of the line that best fits the data cluster (see Figure 3(b)).



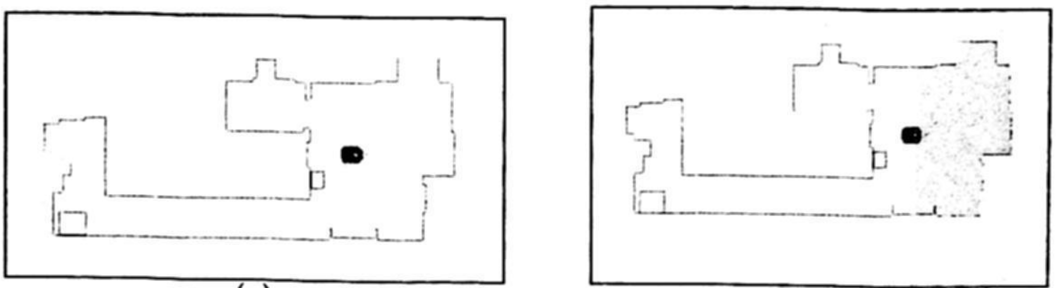
(a) (b)

Fig. 3. Clusters and breakpoints (a). Line found (b).

3 Experiments and Results

All the experiments were conducted both on the XidooBot robot, a LRF-equipped P3AT robotic platform and in the robot simulator provided by its manufacturer (see Figure 4). We have evaluated our qualitative approach by letting the robot to explore the environment in Figure 1. From a starting position (x, y, θ) (see Figure 5(a)) the robot acquired range information using its laser range finder (shown in Figure 5(b)).

Fig. 4. XidooBot.



(a) (b)

Fig. 5. Starting position (x, y, θ) (a) and the measurement acquisition (b).

The actual data readings are shown in Figure 7. The laser sensor of our robotics platform acquires 181 equally spacial angular readings for angles from $-90°$ to $90°$ with respect to the instantaneous robot orientation (see Figure 6 for definition of the robot-centered coordinate system).

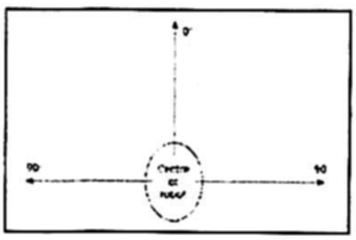


Fig. 6. Robot-centered coordinate system.

Figure 8 shows the decomposition that the clustering algorithm obtains for sensor data in Figure 7. As it is shown, three clusters are identified. Clusters identification depends in the threshold parameter of the Borges *et al.* [11] algorithm.
For each cluster, we apply the *IEPF* algorithm to estimate the parameters of all

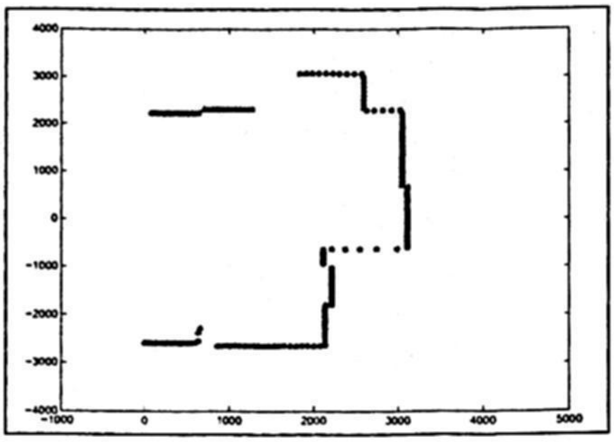
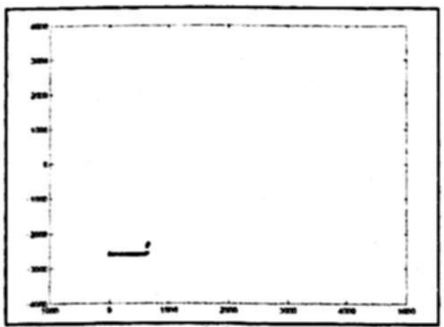
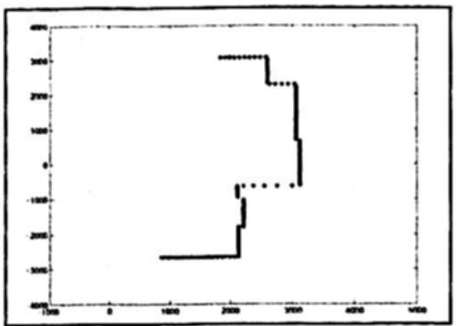


Fig. 7. Data acquired by the robot.


(a)


(b)

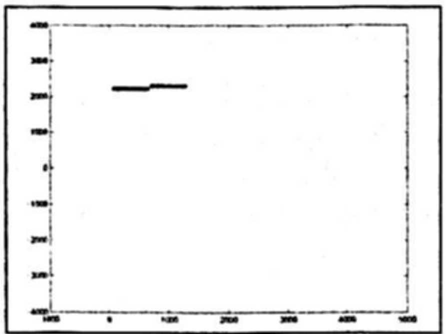

(c)

Fig. 8. Data clusters identified for data in Figure 7. Data cluster 1 (a). Data cluseter 2 (b). Data cluseter 3 (c).

the straight line present in the cluster under analysis.
In Figure 9 we represent the lines obtained when the above procedure has been applied. An overlay of the actual sensor data and the wall models is shown for comparative purposes in Figure 10.

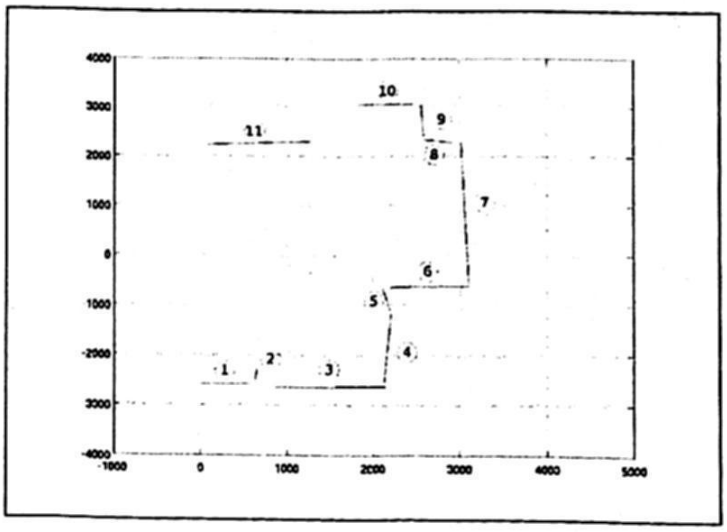


Fig. 9. Line model obtained from sensor data in Figure 7.

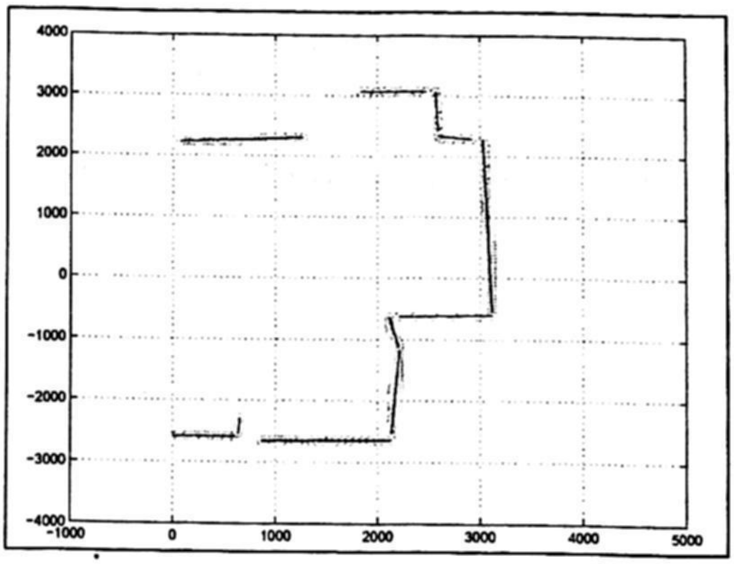
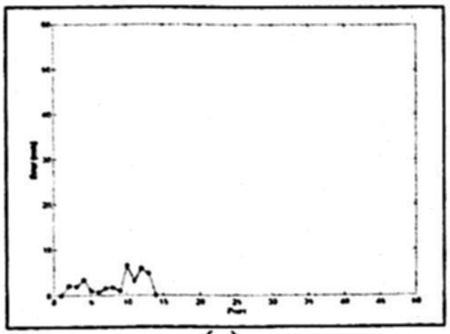
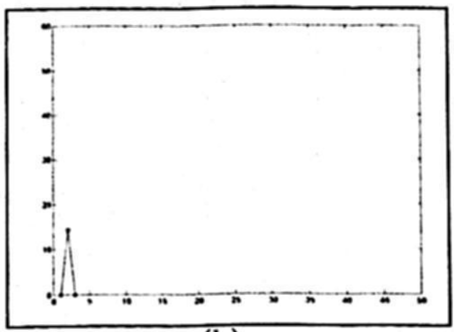


Fig. 10. Comparison between actual sensor data and the scenario model obtained.

3.1 Results Analysis

For each line detected we computed the modeling error as the euclidean distance between each point detected to the associated line (see Equation 1). From this information we have identified different behaviors of the error function that could arise when modelling on environment. Lines 1,2 and 10 present a similar behavior with regard to the modeling error function. They present a small error magnitude explained because they are short line segments. Figure 11 depicts this behavior.


(a)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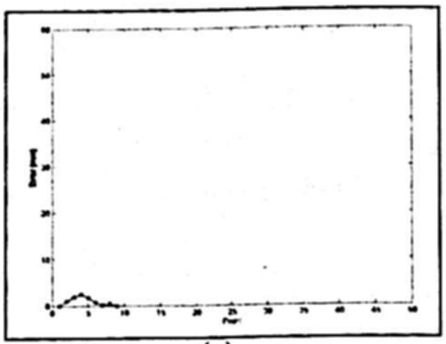
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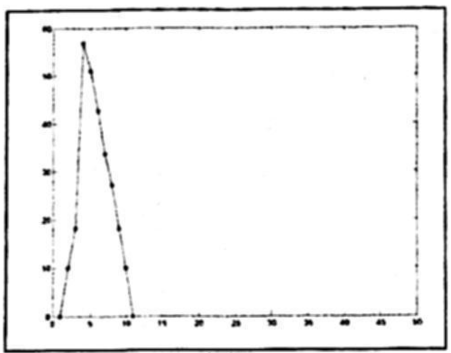
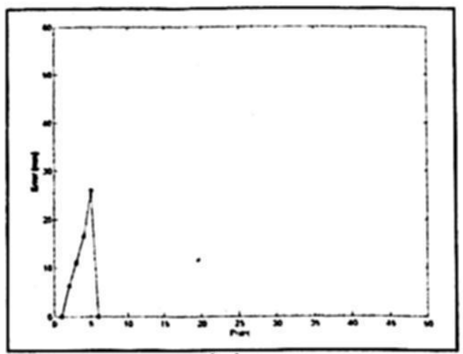
Fig. 11. Lines with a small modeling error. Line 1 error (a). Line 2 error (b). Line 10 error (c).


(a)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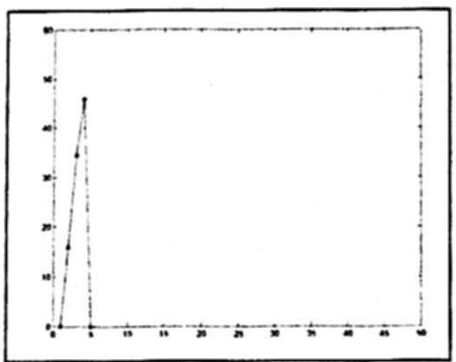
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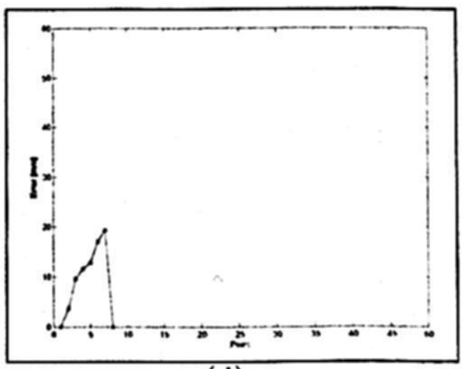
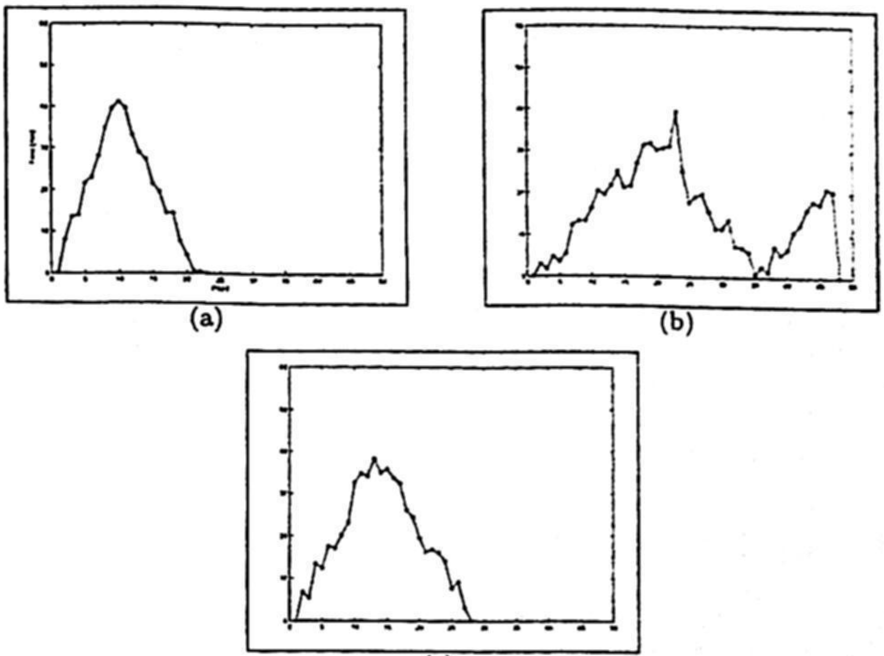

(d)

Fig. 12. Lines where end has not been detected accurately. Line 5 error (a). Line 6 error (b). Line 8 error (c). Line 9 error (d).



(a) (b) (c)

Fig. 13. Lines with an error trough all the line segment. Line 4 error (a). Line 7 error (b). Line 11 error (c).

$$Error_i = \frac{|m_j x_i + (-1)y_i + b_j|}{\sqrt{m_j^2 + 1}} \tag{1}$$

with:

x_i, y_i being the data coordinates associated to the j-th line
m_j, b_j being the slope-intercept parameters to the j-th line

A second group of lines (lines 5,6,8, and 9) present a modeling error significantly larger in one end of the line segment than in the other. This behavior is caused by a bias in the detection of the end where the larger error occurs. We show this in Figure 12.

Figure 13 depicts a third behavior. In the group of lines including lines 4,7 and 11, there is an error through all the line segment. That is originated because two wall were merged into a single line model. Even if this seems to be an inconvenient of our method, we can reduce the problem by increasing the *IEPF* algorithm sensitivity.

Figure 14 shows line 3 modeling error. This behavior is different from the other three groups. Error is not significant but it is present all along the line segment. In fact, it is the longest segment that has been modeled using a single straight line. That is the behavior that we could expect if we explore a typical scenario in indoor robotics. For all the above cases, error modeling for the maximal modeling

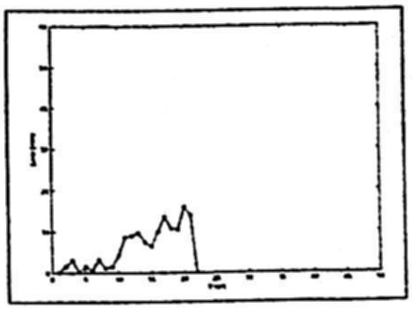


Fig. 14. Expected typical behavior modeling-error in indor environments (line 3).

deviation is 56.86 mm.

4 Conclusion and Perspectives

We have presented a geometrical approach to map building of flat indoor environment. Our method is based in the interpretation of laser sensor reading and its modeling by six-parameters straight lines model. We have detailed the elements and the algorithms used for this task. We have also analyzed our results and we have grouped the behavior of the line composing the model or our scenario. The approach works well as we have shown qualitatively in our paper. Future work will included an analysis of the modeling error when the robot executes its navigation in larger environments.

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