Semantic goal-direct exploration approach

1st Name Lastname, Name Lastname, Name Lastname, Name Lastname, Name Lastname
Institute of Informatics
Federal University of Rio Grande do Sul
Porto Alegre, Brazil
lastname, lastname, lastname, lastname, lastname@inf.ufrgs.br

***Abstract*—TO DO.**

***Index Terms*—TO DO.**

I. Introduction

Visiting a place for the first time is a daily activity for human beings, and exploration is a necessary skill and really important in these cases. Usually, we observe the unknown environment to find and recognise as many exploration cues as possible, such as signs, labels, maps, and doors. Then our high-level reasoning process these cues, and we can infer additional information that is used later during the exploration. Through this process, humans are efficient when exploring unfamiliar places.

Exploration is as important to mobile and autonomous robots operating in unknown environments as it is to humans, and it has been extensively studied by the robotics community. Many approaches decide where to go based on metrical cues, like the shortest distance to unknown areas and nearest or largest frontiers [1]. Other strategies focus on finding regions that improve localisation, like detecting loop closures, in order to facilitate the SLAM process and to build a more precise map of the environment [2], [3]. Still, this decision of where to go usually exploits structural characteristics of the map (e.g. its shape) and the path traversed by the robot, while not considering the semantics of the environment and the objects that it contains. The research community has recognised the limitations of such purely geometric maps and metric planners, leading to increased interest in enhancing the robot's autonomy and robustness [4].

Nowadays, mobile robots are gradually dealing with more complex tasks that require a greater understanding of the environment, in which exploration is vital for the success of the operation [5]. For instance, if you ask a domestic robot to bring you a glass of water, it would be nice if the robot was capable to deduce that the glass is in the kitchen and that the bottle of water is inside the fridge. Therefore, robots must be able to reason over their readings, infer new knowledge, and increase their level of abstraction over time [6]. All this necessity has spawned a meaningful and growing branch of work called semantic robotics [4]. Semantics is the study of meaning, concentrating on the relation between words and world [7]. In the field of robotics, semantics consists of associating meaning to geometric entities in a robot's surroundings.

Identify applicable funding agency here. If none, delete this.

Due to the benefits of semantics, in recent times the robotics research community has proposed new exploration techniques for indoor environments. The goal-direct exploration aims to find an object or a specific area instead of visiting the whole environment. Door numbers, labels, objects and even parts of the environment are being used as visual cues for goal-direct exploration approaches, since complementary information may be inferred from them. Large buildings, for instance, are divided in many small rooms, and usually comply with a standard of labelling each room [8]–[12]. It is used to guide people in finding a room without exploring the whole environment. Once the underlying standard is registered, one can make the best decision based on it.

In this paper, we present a novel semantic goal-direct exploration approach based on door label analysis. The proposed approach extends previous works in exploration using global graph representation and local potential fields, that efficiently propagates the attraction of goals in the environment while smoothly guides the robot avoiding obstacles [3]. The core of our novel approach is to semantically analyse door labels, i.e. rooms identification numbers, in order to define intermediary goals that lead the robot to efficiently find a goal-door (with location unknown). The semantic analysis is made over regions of the map, which is segmented using spatial density information [13]. The main contributions of this paper are:

- a novel semantic planner that reads numbers from door labels, and processes them to infer their semantic information to use as exploration clues. Examples of such information are if the number is *odd* or *even*, if a number sequence is *decreasing* or *increasing*. Given a goal-door as a query that needs to be reached, our method indicates which direction is most likely for it to be.
- a semantic goal-directed exploration system, that does not require any *a priori* map or representation of the building, any training step or preparation, nor any labelling standard guide.

The remainder of this paper is organised as follows. After reviewing the literature in Section II, in Section III we describe the proposed system, explaining how our semantic planner consider the door labels as exploration cues in order to reach the goal-door. Next, in Section IV we introduce the experimental setup and compare our experimental results with results from other exploration methods. We conclude our paper in Section V, discussing the demonstrated outcomes.

II. Related Work

Exploration is a problem that has been studied for many years in the field of robotics. The approaches proposed to deal with this problem can be divided into two fundamental groups regarding their objectives. First, approaches that aim to explore the whole environment, usually finishing when there are no unfamiliar spaces reachable by the robot [14], [15]. Second, approaches that aims to reach a goal in the environment, such as an object or a room. Given that our system is within the second group, the discussion presented below concentrates on goal-direct of exploration methods.

The papers that are reviewed in this section use semantics to improve their findings. Some of them use a semantic map, whereas others use semantic properties of objects. The system proposed by Aydemir et al. [16] focuses on a large-scale environment, where the robot should find objects using mainly visual sensing. They affirm that rather than performing an exhaustive search in the area, their system could find the object directing the robot to search towards areas that are more likely to lead to the object. The probability is calculated considering extracted semantic cues from appearance, geometry, topology of the environment, and general semantic knowledge of the indoor space. They showed that the results improved drastically after including a semantic description in their search system.

Differently, the framework proposed by Veiga et al. [17] searches for objects in domestic environments. It is composed by a system that perceives the query object in RGB-D images through an inference process and using sensor information. The outcome of this process, called knowledge, is saved and updated in a semantic map. Experiments in a realistic apartment have shown that their framework works well in practice, being reliable and efficient in its search.

Another significant work that proposed to search objects in domestic scenarios is Rogers' et al. [18]. Contrary to [17] that proposes a modular system, their approach considers the context of the environment. A graph, connecting related places with objects which can be found in those places, is used to predict the presence (or absence) of objects based on the room categories. The reasoning made over the graph, combined with a planner, is used to perform an object search task. Experiments showed that using this approach the robot could find objects in the environment.

The navigation works proposed by Talbot et al. [5] and Schulz et al. [19] are also goal-directed approaches. The idea of a novel abstract map that links symbolic spatial information with observed symbolic information and actual places in the real world was firstly introduced by [19]. This map is used to make inferences about the location of places. Later, Talbot et al. [5] extended the idea of abstract maps, proposing a novel method that defines the topological structure and spatial layout information encoded in spatial language phrases. The system has shown to complete exploration in unexplored environments by travelling slightly further than the optimal path.

Despite the good outcomes from the solutions presented by the above-mentioned papers, there is still room for improvements. Aydemir et al. [16] depends on prior semantic knowledge about indoor spaces that is obtained from databases. Talbot et al. [5] and Schulz et al. [19] depend on a-priori abstract maps. Veiga et al. [17] requires a-priori information to learn about objects and the environment. Aditionally, it uses an object recognition module that is based on the 3D recognition framework of the Point Cloud Library (PCL), which is computationally expensive. Rogers et al. [18] also implemented PCL in order to segment data from RGB-D sensor, continuing to cluster the points, what is a heavy workload for computers.

Our proposed system reads the door label number through a simple computer vision algorithm, and it analyses them to efficiently decide whether it is better for the robot to go further at its direction or change it. It does not require an environment description or other instruction in advance, which is suitable for tasks in unknown environments. Additionally, it is not computationally expensive, and a robot embedded with a simple computer and RGB camera can execute it.

III. Semantic goal-directed exploration approach

In this section we detail our semantic exploration approach that uses door labels as visual cues, explaining how our system decides where to guide the robot. Section III-A presents an overview of the system, while Sections III-B and III-C describe its modules.

A. Overview

Our proposed system is a goal-directed exploration, i.e. it guides the robot through an unknown area until it finds an objective. It was developed to be used in buildings with many rooms identified by door labels and without any a-priori knowledge of the environment. The specific objective to be reached is a goal-door, that in most cases is labelled as a number. An example to illustrate the use of our system is a robot that delivers food. From the restaurant until the destination building it can use Google Maps and GPS to navigate through the city, but once inside the building there is no map. Therefore, it has to explore the environment to reach the goal-door and finish its task.

Our system is composed of four modules: Mapping, Image Processing, Map Segmentation and Semantic Planner. The module Semantic Planner, presented in Section III-C, is the core of our contribution, and requires a base system to work, composed by the first three modules that are discussed in Section III-B. The first of these three modules aims to build a 2D grid map of the environment using the Histogramic In-Motion Mapping (HIMM) technique, that takes as input the readings of a 180° laser sensor. The next module processes the images taken by an RGB camera, analyses them to recognise the number of door labels, and include these numbers on the map at the same pose that they are in the real world, left or right wall. The third module is responsible for segmenting the free space of the grid map according to its free area, using the Kernel Density Estimation (KDE) approach introduced by our group [13]. This module also assigns, to each segment, the door labels number found on it. The last module guides the robot during the environment exploration, always giving more preference to regions that are more attractive, i.e. likely to contain the goal-door. The robot moves towards this region that is most attractive following the Boundary Value Problem (BVP) [1] that is calculated over the grid map and the Voronoi diagram [20].

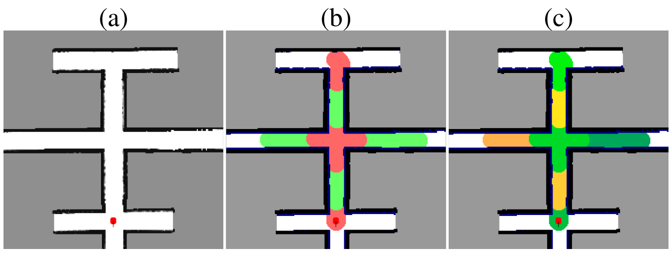

Fig. 1. Example of our segmentation module outcome. In (a) the free cells are represented by the white area in this 2D grid map and the robot is the red dot. Our KDE-based segmentation module groups the free area according to the Eq. 4 in segments, i.e. a set of adjacent free cells that have the same KDE. In (b) there is a partial segmentation of (a), in which the free area was segmented into either red or green. Although some segments in (b) have the same kind, red or green, each segment has a different identification, as illustrated by (c).

B. Mapping, Map Segmentation and Image Processing

As the robot, equipped with a laser range-finder, moves through the environment, it obtains a set of measurements that are used as input to the HIMM method in the mapping module. It aims to build a 2D occupancy grid map $\mathbf{M}$ of the environment [21], Fig. 1-(a). Over $\mathbf{M}$ we also compute the Voronoi diagram to have the centre cells of the free spaces. Based on that, the BVP exploration moves the robot towards the chosen direction avoiding obstacles.

The segmentation module is executed simultaneously while the robot is moving through the environment and updating the map $\mathbf{M}$. It aims to divide the free space into multiple regions according to the area of the free cells, as shown in Fig. 1-(b). Thus, when dealing with segmented regions, it is easier to manage a region as a unique segment, instead of dealing individually with all cells that belong to it, Fig. 1-(c).

For this purpose, our segmentation module uses the KDE approach. The $K(\cdot)$ is an uniform kernel that computes the area of the free space region covered by it, defined as

$$K(d) = \begin{cases} a & \text{, if } d \leq r \\ 0 & \text{, otherwise,} \end{cases} \tag{1}$$

where r is the radius and a is the height of $K(\cdot)$, and d is the distance from the current cell being measured, $\mathbf{c} \in T$, to the centre of the kernel, cell $\mathbf{c}_k \in \mathbf{M}$. $\mathbf{T} \in \mathbf{M}$ is a subset of cells that are within the area of the kernel. For a given cell $\mathbf{c}$, $Q(\cdot)$ tests whether it is free, and is presented as

$$Q(\mathbf{c}) = \begin{cases} 1 & \text{, if } \mathbf{c} \text{ is a free cell} \\ 0 & \text{, otherwise.} \end{cases} \tag{2}$$

Combining the previous function into the KDE approach, we can calculate the kernel density. For the cell $\mathbf{c}_k$, its free space $\Psi(\cdot)$ is computed by

$$\Psi(\mathbf{c}_k) = \sum_{\mathbf{c}}^{\mathbf{T}} Q(\mathbf{c}) K(\|\mathbf{c} - \mathbf{c}_k\|). \tag{3}$$

According to Eq.2, when unknown cells are found within the kernel area, it is still possible to compute $\Psi(\cdot)$. Therefore, once unknown cells return zero from Eq.2, $\Psi(\cdot)$ can differentiate density measures when there are obstacles surrounding $\mathbf{c}$ and decrees the area of the kernel.

Assuming that our segmentation module considers different sizes of free areas, and given that Eq.3 calculates the free area surrounding a cell $\mathbf{c} \in \mathbf{M}$, $\Psi(\cdot)$ can be used in our segmentation module as

$$\Upsilon(\mathbf{c}) = \lfloor \Psi(\mathbf{c})/\delta \rfloor \tag{4}$$

where δ is the threshold that defines how many different sizes of free areas are considered by the segmentation module. For instance, if $0 \leq \Psi(\mathbf{c}) \leq 800$ and $\delta = 400$, Eq. 4 segments free areas in only two different sizes, as illustrated by Fig. 1-(b). On the other hand, if $\delta = 200$, it segments in four sizes. Therefore, a high δ means Eq. 4 considers few different sizes, whereas a low δ is the opposite.

We define a segment $\mathbf{s}$ as a representation of a group of free and adjacent cells from $\mathbf{M}$ that have the same $\Upsilon(\cdot)$. Fig. 1-(c) demonstrate different segments, in which each one has a different colour. For example, $\mathbf{c}_0$ and $\mathbf{c}_1$ are two free and neighbouring cells in $\mathbf{M}$. If $\Upsilon(\mathbf{c}_0) = \Upsilon(\mathbf{c}_1)$, then both belong to the same segment $\mathbf{s}_0$. Otherwise, a new segment $\mathbf{s}_1$ is created and $\mathbf{c}_1$ is associated to it. Therefore, the segmentation of free adjacent cells from $\mathbf{M}$ is based on Eq. 4.

The image processing is the last module that completes the basis of our exploration system. It aims to recognise a door label number that may be in a RGB image. Our intention is to use one well known existing text recognition approach [22]–[24], since this is not the focus of our work and any algorithm could be used. We have chosen the work proposed by [24] due to its real-time recognition aspect, and its robustness against noise and low contrast of characters.

In our system, for a given image $\mathbf{I}$ that was captured by the robot at cell $\mathbf{c}$, the algorithm returns a list $\mathbf{L}$ of recognised doors number. Given that the goal of labelling rooms is to provide an unique door label for each of them, we assume as unlikely the fact of a building having two or more rooms with a same door label. After having $\mathbf{L}$, it must be merged with the doors number list of the segment of $\mathbf{c}$. For this process, it is important to define $\mathbf{s_c}$ as the nearest segment of a cell $\mathbf{c}$, and $D(\cdot)$ a function that returns the doors number list of a segment. Thus, each door number $l \in \mathbf{L}$ is included in the

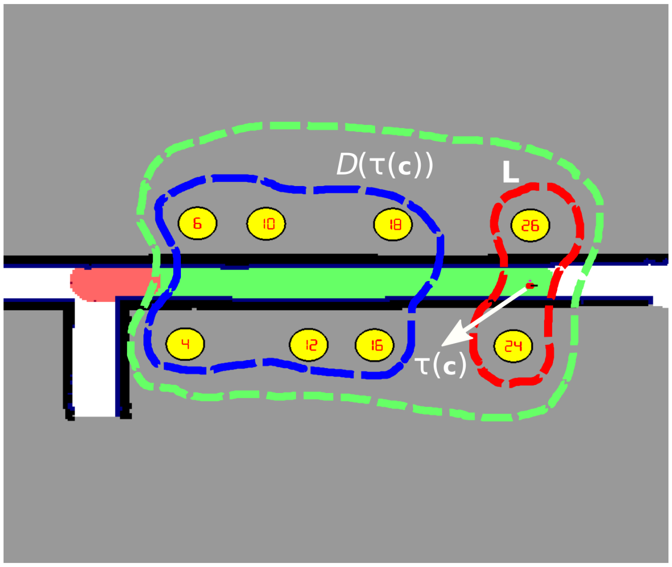

Fig. 2. THIS FIGURE HAS NOT BEEN REFERENCED.

doors number list of $\mathbf{c}$ segment, $l \cup D(\mathbf{s_c})$. Each l has a number of occurrences, that is increased by one each time it is recognised by the image processing algorithm. In case of l already exists in $D(\mathbf{s_c})$, then both number of occurrences are summed.

C. Semantic Planner

Our semantic planner is composed by three different factors, in which two of them are semantic-based, whereas the last one is metric-based. The combination of them leads to a planner that is neither exclusive semantic nor metric, and therefore it can still indicates which is the most likely direction to be explored by the robot even when one of them is insufficient. The factors are presented individually, beginning with the semantic-based factors and finishing with the metric one. This section is concluded with the explanation of how these three factors are combined in order to provide a final value.

To continue the exploration process while the goal-door is not found, our system guides the robot towards a region that is more likely to have it. To decide the best direction to go, this module calculates the attractiveness factor $\varphi(\cdot)$ of candidate cells, that is the outcome of the combination between the three factors presented earlier. Those candidate cells are the ones in the centre of the free space, i.e. in Voronoi, and within the boundary between visited and not visited cells. The visited ones are defined as the free cells that are within the $K(\mathbf{c}_r)$, where $\mathbf{c}_r$ is the robot's pose, whereas the remaining are the free ones that are not close enough to the robot.

To the explanation of this section, it is important to first introduce some variables. Given the set of candidate cells $\mathbf{C}$, the semantic planner decides which has the highest $\varphi(\cdot)$, and then the robot can be guided towards it.

1) Odd and even numbers: This factor considers the characteristics of a door number being *even* or *odd*, an information that is not explicitly available in the environment but can be inferred. The core of this factor is based on the idea that if a goal-door number g is even, it is more likely to it be in a segment that has a high even belief than in a segment with high odd belief.

Every segment $\mathbf{s}$ has these both beliefs, and they represent the confidence of $\mathbf{s}$ to have even and odd number doors. For $\mathbf{s}$, $E(\mathbf{s})$ and $O(\mathbf{s})$ are its even and odd beliefs, respectively, and they are calculated by

$$\begin{aligned} E(\mathbf{s}) &= \min(D_e(\mathbf{s})\beta, 1) \\ O(\mathbf{s}) &= \min(D_o(\mathbf{s})\beta, 1), \end{aligned} \tag{5}$$

where $D_e(\mathbf{s})$ and $D_o(\mathbf{s})$ are the even and odd door numbers from the door list of $\mathbf{s}$, respectively, and β is an influence factor.

We can calculate the difference between these two beliefs regarding g as

$$\begin{aligned} \zeta(\mathbf{c}) = &\overbrace{\Big(E(\mathbf{s_c}) - O(\mathbf{s_c})\Big)H(g)}^{\text{Even term}} \\ &+ \underbrace{\Big(O(\mathbf{s_c}) - E(\mathbf{s_c})\Big)(1 - H(g)).}_{\text{Odd term}} \end{aligned} \tag{6}$$

where the function $H(\cdot)$ tests whether a given goal-door g is *even*. It is defined as

$$H(g) = \begin{cases} 1 & \text{, if } g \text{ is even} \\ 0 & \text{, otherwise} \end{cases} \tag{7}$$

Now, the parity component $\tau(\cdot)$ is defined as

$$\begin{aligned} \tau(\mathbf{c}) = &\Big(\zeta(\mathbf{c})\, \|\zeta(\mathbf{c})\|\Big) \\ &+ \underbrace{E(\mathbf{s_c}))H(g)}_{\text{Even term}} + \underbrace{O(\mathbf{s_c})(1 - H(g))}_{\text{Odd term}} \end{aligned} \tag{8}$$

2) Decreasing and Increasing Sequence: Ja fica aqui uma reviso (ler no tex e nao no pdf por causa dos acentos), o inicio do Odd and Even agora pra mim no faz muito sentido, pq ele explica que pra continuar tem que pensar. Eu acho que o primeiro paragrafo deve ser antes de citar os itens. Aquilo ali o global, puxa pra antes, criar ali um termo pra atratividade total. A parte que efetivamente tem que ficar dentro do item, no segundo paragrafo, a partir de "The ideia of this factor..." antes disso, algo global, falar dos candidatos, de onde eles vem, que eles vo ter uma atratividade e que ela vai ser composta de alguns elementos, ai vem Elemento Paridade, Elemento Direo, Elemento Distancia Fisica e finaliza com a juno dos trłs elementos na atratividade :D

Ingles nivel terceira serie, formulas tbm. Mas vai te ser util pra escrever acho. Comea escrevendo o que a gente quer aqui, depois como.

The main idea is determine to each candidate cell $\mathbf{c} \in \mathbf{C}$ its *Direction Attractiveness* $WW(\mathbf{c})$. To do this, we need first determine in which direction RR the cell $\mathbf{c}$ point, this means, the direction to go out of the visited areas. We determine this using a gradient, each neighboor cell from $\mathbf{c}$ is setted to be 1 if is visited or 0 if is unvisited.

After we need extract some features from the segment $N(\mathbf{c})$. we need determine in which direction FF the door numbers $l \in N(\mathbf{c})$ increasing. Together with the direction we have a norm GG that can be interpreted as a belief. To extract this vector (direction FF and norm GG) we need sum all vectors formed between $l, l^{'} \in N(\mathbf{c}) \mid l \neq l^{'} \wedge\ l < l^{'}$. From this sum we can determine $FF(N(\mathbf{c}))$ and $GG(N(\mathbf{c}))$. The norm $GG(N(\mathbf{c}))$ is normalized using the maximum between $PARAM$ and amount of vectors (no sei como escrever, seria $|(l, l^{'} \in N(\mathbf{c}) \mid l \neq l^{'} \wedge\ l < l^{'})|$.

So, the difference TT is

$$TT(c) = \begin{cases} KK(RR, FF(N(\mathbf{c}))) & \text{, if } g > BIGGER \\ KK(RR, FF(N(\mathbf{c})) - \pi) & \text{, otherwise} \end{cases} \tag{9}$$

been $KK(aa, bb)$ the minimum difference between angles aa and bb. The $SMALLER$ and $BIGGER$ the smaller and bigger door numbers (respectivamente) from all $l \in N(\mathbf{c})$.

ai esse valor TT e feito a formula la do pra dar algo entre -0.5 e 0.5, e ai fica

$$WW(c) = \begin{cases} 0.5 & \text{, if } SMALLER < g < BIGGER \\ 0.5 + \frac{TT(g)GG(N(\mathbf{c}))}{2} & \text{, otherwise} \end{cases} \tag{10}$$

3) Physical distance: !!!!!!!!!!!!!!!!!
!!!

KINDIN EM TEMPO REAL: No fala fronteiras, fala em candidatos, os c E C. E le minha reviso ali atras sobre o inicio do texto nessas partes. Acho que tem que mudar bastante. Atualizei a tabela com a segunda porta, e ja comecei a atualizar com a terceita. (Boa noite!) [DORME]

The last factor that composes the attractiveness calculus is the physical distance between the robot and the frontiers. It was introduced above that the Voronoi skeleton is calculated to have the centre of the free space, the safer region to move the robot. The BVP guides the robot towards the frontiers, but always keeping the robot as near as possible to the Voronoi cells.

Given that the candidate cells are over the Voronoi, as well as the robot, we compute the shortest distance between them through the Voronoi cells.

$\varphi(\mathbf{c}) = \tau(\mathbf{c}) + \Omega(\mathbf{c}) + \alpha\Gamma(\mathbf{c})$

In the end, the robot will move towards the cell $\mathbf{v} = \max(\varphi(\mathbf{c})), \forall\ \mathbf{c} \in \mathbf{C}$.

IV. Experiments and Results

This section presents the setup of our experiments and the simulators used, Section IV-A, the methods that we are examining in contrast with ours, Section IV-B, and the comparison between results from our method and from others, Section IV-C.

A. Experiment Setup

The evaluation of our system was made through the comparison with the traditional BPV exploration and a greedy approach in [REAL AND] simulated indoor environments. The simulated experiments were performed in [AMOUNT] scenarios, and the Table I presents their details. The MobileSim Simulator as used, as well as a Pioneer 3-DX mobile robot equipped with a SICK LMS 200 laser ranger-finder and an RGB camera.

TABLE I
@#@#@#@ TO DO @#@#@#@

Name	**Size**	**Amount of Rooms**
Scenario A	AAA	AAAA
Scenario B	BBB	BBBB
Scenario C	CCC	CCCC

The MobileSim simulates a Pioneer 3-DX, providing the robot's odometry information and its laser sensor readings, but for our tests, the information from doors is missing. Therefore, we developed a simulator that returns the door number as soon as the robot is in front of a door. Our simulator has the list of door labels, with the number and pose of each one, of the map that is used by MobileSim. Then, as the robot moves through the map on MobileSim, our simulator provides the door number in case of the robot to be in front of it. In other words, our simulator works as the robot's RGB camera, providing the door number if an image registers it.

B. Comparative Methods

We are comparing our method with two other ones. The first is the BVP [1], that is adapted to our scenario of goal-direct exploration. The first change stops the exploration if the goal-door is reached by the robot, while the second one is about the frontier. The original BVP considers as frontier the boundary between free and unknown cells.

C. Results

TABLE II
AMBIENTE "DUPLOS"

Door	Method	Min (m)	Max (m)	μ (m)	σ (m)
9	Greedy	50	254	124	96
	Ours (10)	34	155	111	54
	Ours (20)	**30**	**141**	**109**	**44**
60	Greedy	**87**	246	130	60
	Ours (10)	117	146	131	**9**
	Ours (20)	104	**143**	**123**	14
127	Greedy	57	274	163	64
	Ours (10)	57	166	105	30
	Ours (20)	57	**164**	**90**	**29**
132	Greedy	**71**	**221**	**182**	48
	Ours (10)	196	249	230	**16**
	Ours (20)	189	330	236	39
159	Greedy	50	254	124	96
	Ours (10)	34	155	111	54
	Ours (20)	30	14	109	44
999*	Greedy	50	254	124	96
	Ours (10)	34	155	111	54
	Ours (20)	30	141	107	45

TABLE III
AMBIENTE "IGUAIS"

Door	Method	Min (m)	Max (m)	μ (m)	σ (m)
115	Greedy	**71**	240	151	74
	Ours (10)	93	228	169	**37**
	Ours (20)	92	**177**	**137**	39
116	Greedy	46	265	100	90
	Ours (10)	46	**252**	**97**	**85**
	Ours (20)	46	265	142	87
218	Greedy	54	**231**	**166**	**78**
	Ours (10)	**46**	354	213	136
	Ours (20)	74	355	237	120
?	Greedy	71	221	182	48
	Ours (10)	196	249	230	**16**
	Ours (20)	189	330	236	39
?	Greedy	50	254	124	96
	Ours (10)	34	155	111	54
	Ours (20)	30	14	109	44
?	Greedy	50	254	124	96
	Ours (10)	34	155	111	54
	Ours (20)	30	141	107	45

V. CONCLUSION

REFERENCES

[1] E. Prestes, P. M. Engel, M. Trevisan, and M. A. Idiart, "Exploration method using harmonic functions," *Robotics and Autonomous Systems*, vol. 40, no. 1, pp. 25 – 42, 2002.

[2] L. Carlone, J. Du, M. K. Ng, B. Bona, and M. Indri, "An application of kullback-leibler divergence to active slam and exploration with particle filters," in *Proc. of IROS 2010*, oct. 2010, pp. 287–293.

[3] V. A. M. Jorge, R. Maffei, G. S. Franco, J. Daltrozo, M. Giambastiani, M. Kolberg, and E. Prestes, "Ouroboros: Using potential field in unexplored regions to close loops," in *Proc. of ICRA 2015*, 2015.

[4] C. Cadena, L. Carlone, H. Carrillo, Y. Latif, D. Scaramuzza, J. Neira, I. Reid, and J. J. Leonard, "Past, present, and future of simultaneous localization and mapping: Toward the robust-perception age," *IEEE Transactions on Robotics*, vol. 32, no. 6, pp. 1309–1332, Dec 2016.

[5] B. Talbot, O. Lam, R. Schulz, F. Dayoub, B. Upcroft, and G. Wyeth, "Find my office: Navigating real space from semantic descriptions," in *2016 IEEE International Conference on Robotics and Automation (ICRA)*, May 2016, pp. 5782–5787.

[6] R. Barber, J. Crespo, C. Gomez, A. C. Hernandez, and M. Galli, "Mobile robot navigation in indoor environments: Geometric, topological, and semantic navigation," 2018.

[7] N. Riemer, *The Routledge handbook of semantics*. Routledge, 2015.

[8] U. D. of Veterans Affairs, "Room & floor renumbering," 2012.

[9] S. University, "Room numbering guidelines," 2017.

[10] C. W. R. University, "Building and room numbering guidelines," 2015.

[11] U. of Massachusetts Amherst, "Room numbering guidelines," 2012.

[12] B. Haines, "A basic model for numbering your rooms and spaces," 2014.

[13] R. Maffei, V. A. M. Jorge, V. F. Rey, G. S. Franco, M. Giambastiani, J. Barbosa, M. Kolberg, and E. Prestes, "Using n-grams of spatial densities to construct maps," in *2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Sep. 2015, pp. 3850–3855.

[14] A. Quattrini Li, R. Cipolleschi, M. Giusto, and F. Amigoni, "A semantically-informed multirobot system for exploration of relevant areas in search and rescue settings," *Autonomous Robots*, vol. 40, no. 4, pp. 581–597, Apr 2016. [Online]. Available: https://doi.org/10.1007/s10514-015-9480-x

[15] Y. Girdhar, D. Whitney, and G. Dudek, "Curiosity based exploration for learning terrain models," in *2014 IEEE International Conference on Robotics and Automation (ICRA)*, May 2014, pp. 578–584.

[16] A. Aydemir, A. Pronobis, M. Gobelbecker, and P. Jensfelt, "Active visual object search in unknown environments using uncertain semantics," *IEEE Transactions on Robotics*, 2013.

[17] T. S. Veiga, P. Miraldo, R. Ventura, and P. U. Lima, "Efficient object search for mobile robots in dynamic environments: Semantic map as an input for the decision maker," *IEEE International Conference on Intelligent Robots and Systems*, vol. 2016-November, pp. 2745–2750, 2016.

[18] J. G. Rogers and H. I. Christensen, "Robot planning with a semantic map," *Proceedings - IEEE International Conference on Robotics and Automation*, pp. 2239–2244, 2013.

[19] R. Schulz, B. Talbot, O. Lam, F. Dayoub, P. Corke, B. Upcroft, and G. Wyeth, "Robot navigation using human cues: A robot navigation system for symbolic goal-directed exploration," *Proceedings - IEEE International Conference on Robotics and Automation*, vol. 2015-June, no. June, pp. 1100–1105, 2015.

[20] Z. Guo and R. W. Hall, "Parallel thinning with two-subiteration algorithms," *Commun. ACM*, vol. 32, no. 3, pp. 359–373, Mar. 1989. [Online]. Available: http://doi.acm.org/10.1145/62065.62074

[21] J. Borenstein and Y. Koren, "Histogramic in-motion mapping for mobile robot obstacle avoidance," *IEEE Transactions on Robotics and Automation*, vol. 7, no. 4, pp. 535–539, Aug 1991.

[22] H. Zhang, K. Zhao, Y.-Z. Song, and J. Guo, "Text extraction from natural scene image: A survey," *Neurocomputing*, vol. 122, pp. 310 – 323, 2013, advances in cognitive and ubiquitous computing. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0925231213006309

[23] K. Jung, K. I. Kim, and A. K. Jain, "Text information extraction in images and video: a survey," *Pattern Recognition*, vol. 37, no. 5, pp. 977 – 997, 2004. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0031320303004175

[24] L. Neumann and J. Matas, "Real-time scene text localization and recognition," in *2012 IEEE Conference on Computer Vision and Pattern Recognition*, June 2012, pp. 3538–3545.