Mapping Crowd-based Dynamic Blockages for Navigation in Indoor Environments

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***Abstract*— In indoor environments, the presence of people and dynamic objects is ordinary. For autonomous navigation, this can become a challenge because such objects usually exhibit unpredictable behavior that affects the robot's navigation and often requires replanning the path that the robot executes. If the robot system knows a priori that these objects are in certain regions, this can help in decision-making. In this paper, we propose an approach that creates a Crowd-Based Dynamic Blockage layer using semantic information, where this map represents potentially problematic regions that we know contain obstacles. We also propose a strategy to track such obstacles and update the map continuously. Finally, the robot can decide whether a region is suitable to navigate or whether alternative paths must be chosen. Our experiments show that the Crowd-Based Dynamic Blockage can successfully improve planning in this type of environment.**

I. Introduction

During the last decades, autonomous robotics has evolved from static environments, built specifically for a given application, to environments with more dynamic objects, such as warehouses, offices, healthcare houses, markets, etc. In those places, the robot must adapt to them since the possibility of interaction with people and other objects is more likely to occur. This adaptation can bring more autonomy, robustness, and efficiency to the robotic system [1].

An autonomous robot needs to obtain information from its environment and translate it into a sequence of actions determined for it to reach its goal [2]. The amount of variable information makes robotic environments highly unpredictable, especially in close quarters, due to operating close to people. In this case, using higher-level information is a way to better understand the environment and the behavior of those in it.

Several works focus on obtaining and maintaining information about the position of dynamic objects in the environment to use them in the robot's mapping and navigation. In [3], semantic information is used only for grid map construction and marking identified objects. Similarly, in [1] and [4], semantic information is used more straightforwardly to navigate the environment and mark what has been seen. Likewise, approaches to a complete system are referenced in [5] and [6], where information is used to create layers and make navigation decisions on specific situations.

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Besides knowing the position of the objects, it is necessary to know the class of the objects that are identified, to know the characteristics of the objects and how long they usually stay in the environment, e.g., a heavy object (such as large boxes, refrigerators, etc.) in the middle of a path tends to stay for an extended period as opposed to the presence of a person who stays for a short period. Thus, to maintain a well-known environment for autonomous robots, it is prudent to maintain information about the type of object and its location, which can be done by fusing the data obtained through the robot's sensors. Therefore, it is possible to join this information in a semantic map and use it for autonomous robots' navigation, task planning, and exploration.

Information not much explored in previous works is that of areas with dynamic objects that can cause partial blockages and delay the robot's navigation. The idea is not to know precisely the position of dynamic objects, as they tend to change frequently, but the rough region in which they are located and estimate the impact it may cause on navigation in terms of delays if the robot travels there. This situation is the focus of this work. In this paper, we propose a method for constructing dynamic blockages using semantic information about people in the environment. These blockages, called Crowd-Based Dynamic Blockages (CBDB), are weighted for different configurations of people and objects and can be used in traditional planners to make informed decisions. Our main contributions are an approach to maintaining updated CBDB information and a planning strategy using CBDB.

The paper is structured as follows. Section II presents the academic background, Section III describes a system overview of our method, Section IV shows the results of conducted experiments, and Section V summarizes our work and suggests future works.

II. Related Work

Semantic mapping is a widely researched area with differing approaches and for different purposes. In [7], a semantic map is defined as obtaining relevant information in the environment in which the robot is inserted and attaching it to maps being created or other types of objects created. In some cases, its use is for open environments, like in [8], where the authors create a semantic map of the sidewalk and the road. In indoor environments, in [9], the authors build a semantic map from the robot's sensor information and use the robot's information to be able to navigate the environment and plan tasks. This information is assembled into a multi-hierarchical representation. Similarly, the strategies in [3] and [10] perform object detection and classification with the

YOLO technique [11] [12] and place the information in a grid map.

A different approach to constructing the semantic map is made by [13], where the authors address the problem that the robot knows that there are objects around it but does not know what type of object is detected. In [4], a different type of semantic map is built with information from door numbers; thus, a robot can be directed to rooms within the known part of the environment. In [14] and [1], the authors use the object's semantic information to associate locations and orientations where these objects should be to devise a dynamic navigation strategy.

Other works using semantic maps focus on task planning, a well-known area where a sequence of steps is planned for the robot to execute to reach a specific location and fulfill a task. In [15], the authors use a previously created semantic map to solve tasks without human intervention. Instead of having the goal as a set coordinate for the robot, the system sets goals by giving the robot the task of finding an object or entering a room in the environment.

A complete navigation robot system can be made using the strategies above. In [16], the authors built a system using semantic mapping and path planning techniques for use in a wheelchair. The chair can use the grid map to plan its path, and the semantic information is used to iterate between humans and robots, enabling efficient navigation. In [6], the authors use the semantic map information when the robot moves to a new destination, considering that at certain times of the day, it must deviate from an area and take a longer path for safety. In another approach, [5], the authors use the Human-Robot interaction to create layers from the objects checked in the environment so that the robot goes to people requesting their attention or avoids areas where a person is performing tasks that the robot could interfere with. Similarly, in [17], the authors use a layering approach with spatial information to characterize office spaces to create conceptual representations. Our approach also proposes a complete mapping and planning system, as presented below.

III. System Approach

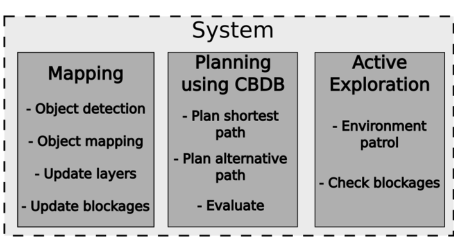


Fig. 1. Overview of the proposed system containing the mapping, the planning, and the exploratory components.

We propose a system for robots equipped with a 2D LIDAR and an RGB-D camera that operate in environments with dynamic objects and agents, such as people. Our system is composed of three major components, as seen in Fig. 1: the mapping of objects in the form of a semantic map describing the CBDB information, a planning strategy using the CBDB where the best path is chosen considering the mapped blockages that cross the robot's way and an exploration strategy which consists of actively moving the robot to the location of current blockages to update them and search for new ones. Next, we present each component in detail.

A. Mapping

The main idea of this component is to map dynamic objects, such as people, in a 2D representation and then evaluate whether the regions containing them are favorable for navigation. For this, we identify and classify objects, geometrically map the environment with a SLAM technique, mark the regions of interest, and evaluate the costs of going through those regions. For the first two tasks, we use YOLO for object detection using camera images[1], and GMapping for building a 2D occupancy grid map from LIDAR information[2], both being well-established solutions in the field of robotics and automation. For this work, only some objects are considered (e.g., person and luggage); other objects that are in the environment are considered unknown to this system. Some of these classified objects are shown in Fig. 2.

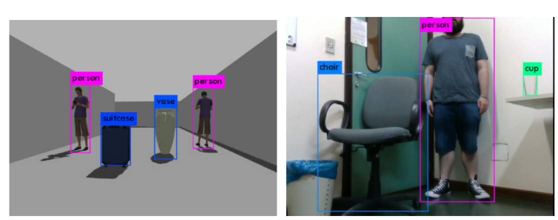
After identifying an object of interest, to obtain its location in the world we calculate an estimated position based on the object's bounding box, determined by YOLO, and the depth information of the pixels associated with the image patch given by the bounding box. The information about the objects in the environment is used to create a layer that maintains control of the regions containing objects over time. In this work, we call this layer *"Crowd-based Dynamic Blockages"*, an example seen in Fig. 3(a).

The original occupancy grid, a lane map, and a semantic map indicating the objects' positions must also be updated before building the CBDB. A complete overview of the layers[3] used in the proposed system can be seen in Fig. 4(a). When an object is detected, positional and semantic information about the object is marked in the semantic map, i.e. a grid map with different colored marks indicating the semantic value, as shown in 4(b). The information on

[1] We use YOLO_v3, a deep learning method for object detection [11].

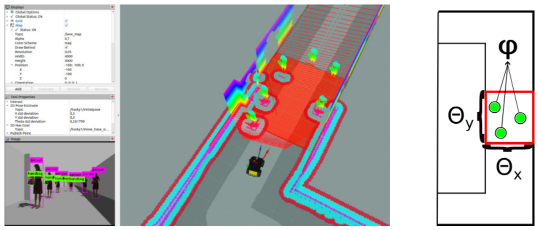
[2] We use the ROS implementation described in `http://wiki.ros.org/gmapping`.

[3] As our proposal focuses on the mapping of dynamic objects, the static mapping of the environment using Gmapping and the creation of preferred lanes for robot navigation were created prior to our experiments.



(a) Simulation (b) Real scenario

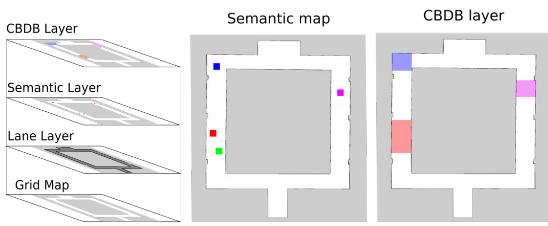
Fig. 2. Example of types of objects detected by the proposed system in simulation and real environments evaluated in our experiments.



(a) (b)

Fig. 3. Example of a CBDB applied over a grid map based on the location of detected objects. (a) Grid with a full blockage marked in red. (b) Values used to compute the weight of a blockage region, where θ_x and θ_y are the dimensions of the area affected by the objects and φ is the number of objects in this region.

the position, the quantity, and the types of objects in the environment is used to create the blockage in the region, shown in Fig. 4(c), which will receive a weight later used for planning.



(a) (b) (c)

Fig. 4. Configuration of the layers used in the system. (a) All four layers in the system. (b) Closer view of the semantic map. (c) Closer view of the resulting CBDB based on the information in the semantic map. Clustered objects generate larger blocking regions, as shown in red.

The dimensions of the blockage region, given by θ_x and θ_y, are defined as the sides of a bounding box containing the positions of objects detected in front of the robot. Information about the number of objects detected by the robot(φ) is required as well, as exemplified in Fig. 3(b). Next, we compute the weight of the region as follows,

$$\gamma = \frac{\varphi}{\alpha \theta_x \theta_y} \tag{1}$$

where α is a weighting factor that sets the difficulty of crossing an area in terms of the number of objects per m^2. The weight is higher in proportion to the number of obstructions in the way of the robot since more turnings are made and more time is spent navigating.

B. Planning

We convert objects detected into weighted blockages in the CBDB layer and give this information to the robot to plan if a crowded path is worth traveling or if it is better to take a different route. First, our system uses A* as the standard planner, but the algorithm is interchangeable, to get the shortest possible path P_{orig}, that can be chosen by the robot considering whether the area is blocked in the CBDB layer, as illustrated in Fig. 5.

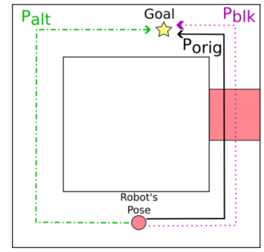


Fig. 5. Example of paths used in the planning process considering the CBDB. P_{orig} is the original path given that no blockage exists, P_{alt} is an alternative path given that the region has a full blockage, and P_{blk} is the same path P_{orig} but with the weight of the partial blockage, w_{blk}.

The impact of the blockage over P_{orig}, which we denominated w_{blk}, is obtained by applying the weight γ over the path section associated with the region, as follows,

$$w_{blk} = \frac{w_R}{1-\gamma} \qquad \gamma < \gamma_{max} \tag{2}$$

where the weight of the blocked region is taken into account when the steps from P_{orig} pass through the created blockage (w_R) need to receive the weight of the blocked region. Considering that the robot needs a feasible space to travel, the variable γ_{max}[4] is used to determine how crowded a region can be before being considered totally blocked.

The updated path regarding the blockage region, P_{blk}, is P_{orig} with an updated cost, as given by

$$cost(P_{blk}) = cost(P_{orig}) + (w_{blk} - w_R). \tag{3}$$

Then, we analyze if the updated path is sufficiently better than an alternative path, P_{alt}, that completely blocks the designed region, as shown in Fig. 5. The decision follows Eq 4. If after weighing the blockage, the cost of P_{blk} is higher than P_{alt}, we select the alternative path. Before selecting P_{blk}, we ensure that its cost must be lower than P_{alt} by a threshold w_{diff}[5]. This parameter was added after observing that deciding between narrow differences produced inconsistent results.

$$Path = \begin{cases} P_{alt} & if\ cost(P_{alt}) < cost(P_{blk}) + w_{diff} \\ P_{orig} & otherwise \end{cases} \tag{4}$$

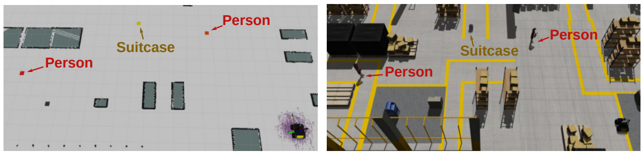
C. Navigation and Object Position Update

To keep the information about blockage regions up-to-date, the robot maintains a list of previously detected objects that need to be evaluated to see if they are still in place and update them if they have moved. An example of objects that need to be analyzed can be seen in Fig. 6, where each has a different color assigned to it.

During the exploration phase, visual information is processed and examined. An algorithm describing the decision-making when encountering an object is shown in Alg. 1.

[4] All the experiments executed in this work set the values of $\alpha = 2$ and $\gamma_{max} = 0,7$

[5] In our experiments, the w_{diff} value was taken as a 350 step difference between the two paths.



(a) (b)

Fig. 6. Example of exploration of desired objects that need to be analyzed and updated. (a) The different class objects marked in the grid map. (b) The real position of the objects in the environments.

When the robot performs the exploration, if no object is found, the occurrence in the grid map is cleaned, and the robot goes to the next destination and repeats the process. When the robot sees more than one object, all objects will be analyzed.

Algorithm 1: Active Exploration Strategy

while *coverage not completed* **do**
  if *object is detected* **then**
    if *detected object is already mapped* **then**
      Update object information
    else
      Clear old object and update new one
  else
    Clear object information
end while

IV. Experiments

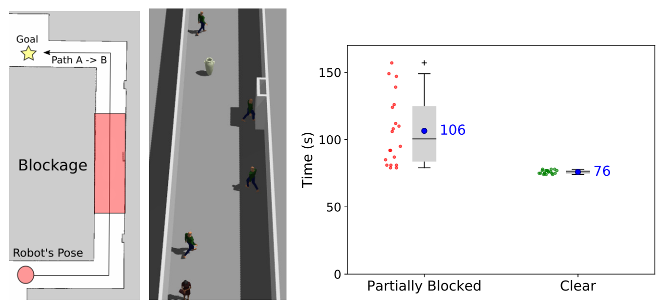
The analysis of our proposal took place through tests with a Pioneer 3-DX mobile robot equipped with a SICK LMS 200 LIDAR and an Intel Realsense D435 RGB-D camera in simulated and real scenarios. Simulated tests were developed using the Gazebo simulation environment with ROS, while tests with the physical robot were performed in the Institute of Informatics building of UFRGS-Brazil. All the simulated experiments were performed in a platform with Ubuntu 20.04 equipped with an AMD Ryzen 5 processor, 48GB RAM, and a GPU Nvidia GeForce RTX 3060. The experiment in the real environment was performed on a platform with Ubuntu 20.04 equipped with an AMD Ryzen 7 processor, 16GB RAM, and a GPU Nvidia GeForce RTX 3060.

Our experimental validation was divided into three parts. First, we performed experiments that analyzed the impact of partial blockages in the robot's path and how knowing such information beforehand leads to better navigation choices. Next, we analyzed the behavior of the proposed algorithm in different situations, observing when the robot decides to take the original shortest path and when it is better to take an alternative longer path depending on the map topology and blockage configurations. Finally, we compared the results obtained with a standard planning strategy[6] and our proposal using the CBDB.

[6]For this, we used the move base package for ROS, which can be found in `http://wiki.ros.org/move_base`

A. Analyzing the impact of people moving in the robot's path

Preliminary experiments were conducted to verify how partial obstructions can hinder navigation, making it slower as the robot needs to adjust its route when encountering obstacles. Simulated tests were done in a corridor-shaped environment, Fig. 7(a), with a blockage region containing dynamic obstacles, represented by people walking through the corridor, and stationary obstacles, represented by office furniture and people standing still, as shown in Fig. 7(b). The robot moved 20 times from one side of the map to the other and returned, reacting to obstacles (which moved independently of the robot's motion). We compared the crossing times of the clear path with the partially blocked path in Fig. 7(c).



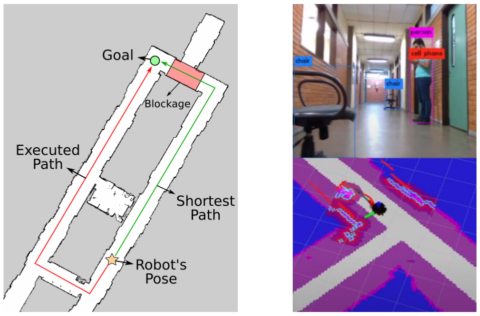
(a) (b) (c)

Fig. 7. Experiments in a simulated corridor environment with partial blockage in the path. (a) The robot repeatedly moves from one end of the corridor to the other and returns. (b) Example of objects present in the partial blockage sector. (c) Box plot comparing elapsed travel time in paths that have a partially blocked zone or clear paths. The red and green dots are the travel times in the partially blocked zone and the clear path, respectively. The blue circle and number indicate the average time for each scenario.

In a fully known environment (e.g., the clear zone), the robot follows the planned path consistently, as seen from the very low variance in the times obtained. On the other hand, we can see that the presence of dynamic obstacles, even without completely obstructing the path, substantially delays the robot's navigation (in the tested case, by about 40%). Therefore, using the information in the CBDB, the robot can plan whether it is worth trying to cross a potentially blocked area or detour to an alternative path.

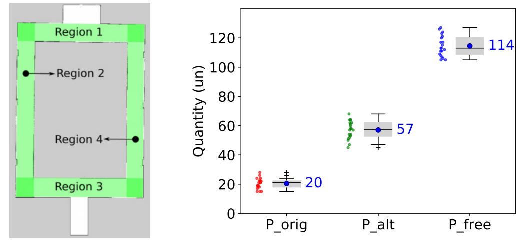
B. Analyzing the navigation's decisions using CBDB

For the second part of the experiments, we analyze how different types of maps and blockage locations impact the decisions of our planning strategy. We first tested the approach in the real-world environment of the Institute of Informatics through a few experiments to observe its practical application. An example of a situation encountered in our tests can be seen in Fig. 8(a), where the shortest path goes through a blockage, and our system decides to take the alternative path. In Fig. 8(b), we can see the robot detecting objects in a corridor in a blockage position. In environments with similar corridor sizes, the differences between P_{blk} and P_{alt} are minor; thus, the method chooses to follow the path without partial blockages, as expected.

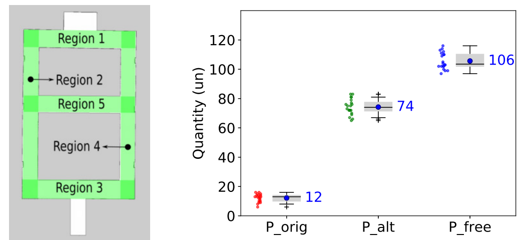


(a) (b)

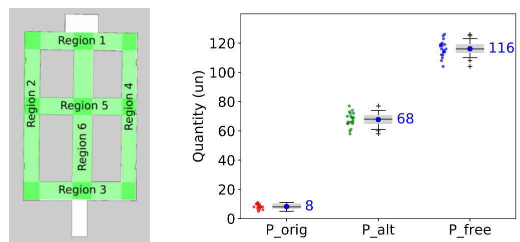
Fig. 8. Experiments performed in the Institute of Informatics. (a) Example of the shortest path calculated and the path executed by the robot after the blockage calculation. (b) Example of dynamic objects observed in the environment that generate a partial blockage in the corridor.



(a) Scenario A (b) Decisions in Scenario A



(c) Scenario B (d) Decisions in Scenario B



(e) Scenario C (f) Decisions in Scenario C

Fig. 9. Results of simulated experiments to analyze planning decisions. Left: scenarios tested in the simulated experiments, with each corridor region marked in the maps. Right: box plots describing the decisions made in each scenario.

Next, we performed multiple sets of simulated experiments in different scenarios. We executed our system in three different scenarios, 20 times each. Scenario A had 192 different configurations of blockages, initial positions, and goals. Due to the complexity of scenarios B and C, we randomly sampled among possible combinations of blockages, initial positions, and goals, these scenarios are shown in Figs. 9(a), 9(c) and 9(e). Each map was divided into regions associated with the corridors. A test configuration was made by randomly selecting regions for the initial pose, the goal, and a blockage region. Due to the high number of tested configurations, we only carried out the planning process and evaluated the results, but we did not perform the complete tests moving the robot in the Gazebo simulator.

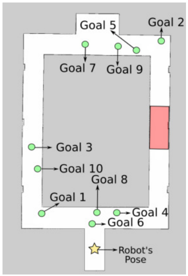
In each test, the robot calculates a path from a source to a destination. If a blockage is in the way of the original path, our system computes how much this blockage affects the plan. Results are shown in Figs 9(b), 9(d), and 9(f). We can see that path P_{alt} was selected with greater frequency than P_{orig}in all the different maps. Because the generation of blockages in the environment is random, most of the time the shortest path is not affected by a blockage. In this case, we consider the path chosen as free, or P_{free}. In other situations (which varied from 40% to 45% of the time, depending on the scenario), the blocking region coincided with some section of the shortest path, and the algorithm had to decide what to do. In this case, in all scenarios, the algorithm most of the time preferred to take the alternative path and avoid the partially blocked region. However, the difference decreases when there are fewer options for alternative paths: in scenario C the choice for P_{alt} is 8.5 greater than for P_{blk} (i.e. 68/8); in scenario B it decreases to 6.2 (i.e. 74/12); and in scenario A it drops to 2.9 (i.e. 57/20). Therefore, when the alternative options are few, it becomes worthwhile to consider traversing the partially blocked regions.

C. Analyzing the complete planning system

In this last experiment, we tested the execution of the complete planning system, performing the decision-making and simulating the robot's motion in Gazebo, while comparing the results with a standard navigation strategy that does not use CBDB. Fig. 10(b) summarizes the obtained runtime results using a configuration system where the blockage is in a specific map region shown in Fig. 10(a). The columns *'CBDB? No'* in Fig. 10(b) describe the results obtained using the standard navigation algorithm, i.e., when the robot does not have the blockage information; the column *'CBDB? Yes'* shows our system's results. We randomly chose 10 random positions displayed on the map. The robot starts from its initial position and travels to goal positions sequentially. Only one blocking region exists on the right side of the map, so some shortest paths between goals do not cross the blockage, but others do.

In addition, two conditions of CBDB information were tested: one with high accuracy and the other with low. In the experiments marked as *'φ set'*, the exact number of obstacles predicted in the CBDB were placed in the blockage area. In the experiments marked as *'φ random'*, a variable amount of obstacles was placed in that region. This means that the number of obstacles was likely different from what was predicted, potentially resulting in a different crossing time than what was initially expected for the robot.

P_{free} represents the choices made where the path to the goal did not pass through the blocked region. P_{orig} repre-



(a)

#	φ set CBDB? No	Yes	Choice	φ random CBDB? No	Yes	Choice
1	26	21	P_{free}	25	22	P_{free}
2	95	84	P_{alt}	100	81	P_{alt}
3	70	73	P_{free}	71	69	P_{free}
4	46	48	P_{free}	46	46	P_{free}
5	74	91	P_{orig}	62	52	P_{alt}
6	80	66	P_{orig}	115	65	P_{orig}
7	87	78	P_{alt}	100	81	P_{alt}
8	85	78	P_{alt}	107	78	P_{alt}
9	130	75	P_{orig}	88	87	P_{orig}
10	74	75	P_{free}	74	75	P_{free}

(b)

#	φ set CBDB? [s] No	Yes	φ random CBDB? [s] No	Yes
Scenario A	76,7	68,9	78,8	65,6
Scenario B	67,2	60,4	66	56,8
Scenario C	52,8	51,4	52,5	51,8

(c)

Fig. 10. Fig. 10(a) are the goals used in one of the experiments, in this configuration the blockage is the red region and the start pose of the robot is represented with the yellow star. Fig. 10(b) shows the results obtained in this experiment, where each row is directly bound to goals in Fig. 10(a). The highlighted rows are the paths chosen that go through a region with a blockage. Fig. 10(c) has the mean times for all configurations on each scenario.

sents the choices made when the calculated cost of the detour doesn't reach the threshold, maintaining the original path, and P_{alt} represents the choices where the robot detours from the blocked region. The paths followed by both algorithms when choosing P_{orig} are virtually the same. However, the time taken to travel through them may be different, which is justified by the fact that the robot has to make real-time adjustments to avoid unpredicted dynamic obstacles.

Fig. 10(c) synthesizes the mean time for each case scenario (e.g. Fig. 10(b) being a fragment of the experiment) for all the maps used. With this, we can compare that on the φ set, scenarios A and B have an average time using the CBDB 11% less than not using it (i.e. 68.9/76.7 and 60.4/67.2). However, scenario C's average time is only 3% lower (i.e. 51.4/52.8). When φ is random, using CDBD in scenario A produces a time that is 17% faster (i.e. 65.6/78.8) and 14% faster in scenario B (i.e. 65.6/78.8). In scenario C, the times were only 2% lower (i.e. 51.8/52.5).

With these results, it is possible to note that when the map has different paths that can be chosen, the gain with the usage of CBDB decreases. In contrast, it is beneficial to use CBDB in environments with long corridors or limited routes.

V. Conclusion and Future Work

In this work, we proposed a system composed of semantic mapping and planning that uses the Crowd-Based Dynamic Blockage layer, our main contribution. Using such information during planning can avoid wasting time going to a blocked path while saving computational resources by pruning costly paths. With our experiments, we observed that a robot navigating a corridor with dynamic objects might take longer time as opposed to empty corridors. Additionally, using our method, we can see that there has been an improvement when evading blocked regions using the previously acquired information.

For future works, we plan to use our system in a more realistic environment while considering more object classes and vast areas. We also consider using the Crowd-Based Dynamic Blockage layer to adjust the robot's position in case of poor localization.

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