Bar Ilan University

M.Sc Proposal

Speeding Frontier-Based Exploration by Using Semantic Labeling

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1 Introduction

The problem of exploring an unknown territory is one of the fundamental problems in robotics. The goal of exploration is to gain as much new information as possible of the environment within a short time. Applications of efficient exploration include search and rescue, planetary exploration [3] and military uses [10].

This thesis proposal deals with making the exploration process faster. Frontier-Based exploration is the most common approach for solving the exploration problem. However, frontiers detection is very hard. We propose a new frontier detection algorithm (section 1.1). In Section 1.2 we propose to use semantic labels in order to speed up the exploration process.

1.1 Frontier-Based Exploration

The most common approach to exploration is based on *frontiers*. A frontier is a segment that separates known (explored) regions from unknown regions. Thus, frontiers are important targets for exploration. Yamauchi [20, 21] was the first to show a frontier-based exploration strategy.

However, frontiers are hard to calculate. Most of frontier detection methods are based on edge detection and region extraction techniques from computer vision. The meaning of the above fact is that in order to detect the frontiers, each time we have to process the entire world map data.

We propose an incremental approach for frontier detection (Algorithm 2). Our proposed algorithm does not have to scan the entire world data for detecting frontiers. It processes only not previously scanned regions.

1.2 Semantic Labeling

The exploration process can also be improved by exploiting a-priori knowledge of the explored environment. In general, exploration of indoor environments like

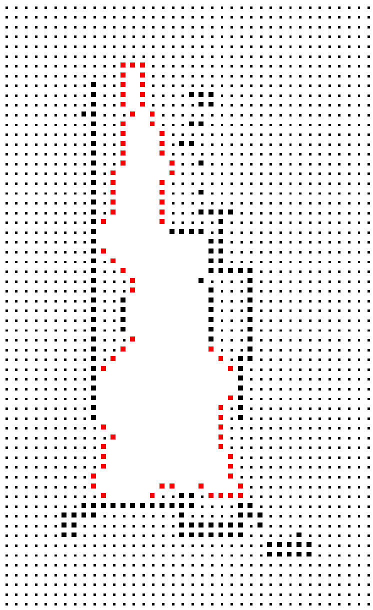

Figure 1: Frontiers detection example (image was taken from [1]).

office building can exploit the fact that most likely, explored objects are rooms which are connected by corridors. In addition, rooms will probably consist of 4 walls, one door and 4 corners with 90 degrees angles. The exploring robot can exploit the above features to improve its navigation (i.e. speed).

In addition, better reasoning about world objects (such as doors, rooms, corridors) can improve the communication between the robot and its operator. Operator-robot communication can be more naturally due to applying *semantic labels* on world objects. For instance, the robot can accept commands such as: “Search behind the desk that is located in the second room from the right side of this corridor“. This capability is called *Semantic Labeling* which involves applying semantic information to the environment.

We propose several heuristics which use such semantic information to enhance the speed of the exploration process not only by performing a smarter environment scan, but also reduce interruptions to the operator.

2 Background and Related work

2.1 Frontier-Based Exploration

The problem of exploring an unknown environment with a single or multi mobile robots has been concerning many authors. There are two aspects that have to be taken care of:

- Deciding on next target to be explored
- Coordinating the team members in order to minimize overlaps

An outline of the exploration process is described in Algorithm 1.

Algorithm 1 Exploration Outline

1: **while** exists any unknown territory **do**
2: allocate each robot a new set of targets
3: each robot visits its target and includes the new data obtained from its sensors
4: **end while**

Yamauchi [20, 21] developed a method that can be used by a team of robots. The robots explore an unknown environment and exchange information with each other when they get new sensor readings. As a result, the robots build a common map (occupancy grid) in a distributed fashion. The map is always being updated until no new readings are available. This work also introduces the notion of a *frontier*. In this method, each robot is heading to the *centroid**, the center of mass, of the closest *frontier*. In this method, all robots navigate to their target independently while they share a common map. Although Yamauchi's method is robust for disconnections, it is clearly not optimal because there is no coordination between the team members. Team members might cover the same area or even interfere with each other and map each other as an obstacle.

Burgard et al. [7] presented a probabilistic approach for coordinating a team of robots. Their method considers the trade-off between the costs of reaching a target and the utility of reaching that target. In order to minimize overlaps between team members, they defined the utility of a target by the size of the unexplored area that can be covered by the robot's sensors upon reaching that target. Whenever a target point is assigned to a specific team member, the utility of the unexplored area visible from this target position is reduced for the other team members. This way a team of multiple robots can minimize overlapping in the coverage area. Their method is centralized in contrast to our proposed work.

Burgard et al. [18] proposed to assign a target destination to each robot in a way that that maximizes the expected map knowledge over time. They proposed a bid-based heuristic. Each robot estimates its utility and cost until arriving various targets. According to this calculation, each robot creates bids. After receiving all bids, a central agent assigns a target to each robot considering minimization of the overlapping coverage of the team members.

Ko et al. [11] presented a decision-theoretic approach to the mapping and exploration problem. Their approach uses an adopted version of particle filters to estimate the position in the other robot's partial map.

Lau [12] presented a behavioral approach. The authors assume that all team members start from a known location. The team members follow the behavior and spread in the environment while updating a shared map. The coordination of team members is achieved by using potential fields. Moreover, frontier-based path planning is used to avoid convergence to local minima.

Sawhney et al. [17] presented an exploration method for both 2D and 3D environments. They showed a novel visibility per-time metric that is being used

*The centroid of a finite set of k points $x_1, x_2, \ldots, x_k \in \mathbb{R}^n$ is defined by:

$$C = \frac{1}{k}\sum_{j=1}^{k} x_j$$

,

by the exploration algorithm. Their method covers nearly the same number of points like other metric method that can be found in literature. However, the time length of the paths is smaller. The outcome is reduced exploration time.

Bouraqadi et al. [6] proposed a flocking based approach for solving the exploration problem. Each robot is acting according to the same set of rules. The rules are prioritized and in case of conflict, the robot chooses the rule with the highest priority. One of their rules (R5) makes the robot navigate towards the nearest frontier.

Berhault et al. [5] proposed a combinatorial auction mechanism where the robots bid on a bunch of targets to navigate. The robots are able to use different bidding strategies. Each robot has to visit all the targets that are included in his winning bid. After combining each robot's sensor readings, the auctioneer omits selected frontier cells as potential targets for the robots.

All the above methods do not use any semantic information. As a result, their exploration speed is slowed down due to not optimal navigating to target.

Moreover, to the best of our knowledge, all these works utilize a standard edge-detection method for computing the frontiers. Thus, our improved frontier detection algorithm can boost all of these methods.

2.2 Semantic Labeling

Over the years, the problem of building accurate maps of the environment from the data obtained from a team of mobile robots have been considered many researchers. However, the question of augmenting such map by semantic information is still open. In addition, using semantic labeling can enhance the operator-robot communication. The communication will become more natural.

Mozos et al. [13, 19] proposed an approach based on supervised learning to determine what is the semantic class that corresponds the pose of a mobile robot. They used AdaBoost to boost simple features extracted from range data and vision into a strong classifier.

Ranganathan et al. [16] presented a model for place recognition that uses objects as its measurement unit. Their model extends the constellation model to 3D. Each object model is learned by a supervised form. In addition, they use the Swendsen-Wang algorithm [4] to solve the correspondence problem between image features and objects during inference.

Althaus et al. [2] used line features to detect corridors and doorways from sonars.

Mozos et al. [14] proposed a technique that uses simple features extracted from laser range scans to train a set of classifiers and in this way are able to label a place given a single 2D laser range observation.

Fox et al. [9] presented a technique which aims to learn background knowledge in typical indoor environments and later on use that knowledge for map building. They apply their approach to decide whether the robot is seeing a previously built portion of a map, or is exploring new terrain.

We intend to build on this work to demonstrate how to use semantic labels in several novel ways. These will improve the exploration speed.

3 Our Proposed Work

In the following section we propose a fast frontier detection algorithm (section 3.1). The proposed algorithm (Algorithm 2) detects all the frontiers but in contrary to other traditional methods, doesn't have to process the entire map cells data. In addition, we suggest several heuristics (section 3.2) that use semantic labeling in order to speed up the exploration process and minimize interruptions to the operator.

3.1 Speed-up Frontier Detection

To our best knowledge, existing frontier detection methods are all based on edge detection techniques taken from image processing and computer vision fields. The problem is that all methods have to process the entire image. However, in the robotics domain, there is a need to scan relativly large images and hence, the above methods suffer from significant processing time.

Instead, we propose to compute the frontiers by an incremental approach, which will be significantly faster. The proposed algorithm processes only regions that were not scanned before. Furthermore, when the algorithm detects that its scan arrives to an unkown region its stops. The reason is that new frontiers will not be found in those regions. New frontiers are found only on boundaries between open spaces and unknown spaces. Therefore, only relevant environment areas are scanned in each iteration of the algorithm.

Algorithm 2 IFD Outline

Require: F_{curr} // F_{curr} is a data-structure that contains frontiers
$F_{new} \leftarrow \phi$
for all frontier $f \in F_{curr}$ **do**
  pop f from F_{curr}
  for all cell $c \in f$ **do**
    start from c, pass only through previously unscanned cells and search for a new frontier
    if new frontier was detected **then**
      insert new frontier to F_{new}
    end if
  end for
end for
return F_{new} // return detected frontiers

Our proposed algorithm (Algorithm 2) is called *IFD* (Incremental Frontier Detector). IFD uses a data-structure, F_{curr}, that contains all detected frontiers so far. F_{new} is a data-structure that contains the output, the detected frontiers. Whenever the algorithm pops out a frontier f from F_{curr}, there are 2 cases:

- The robot didn't move towards f since last execution of IFD. Therefore, there won't be any additional information that can be integrated to the world model. IFD will will keep f for next execution.
- The robot moved towards f. As a result, f is no longer a frontier because the robot reached to f. A new frontier that was sensed beyond f is added to F_{new}.

Only one new frontier can be detected from existing frontier. The reason is that frontiers are either disjoint or equal. Therefore, if one frontier point is detected, there will be only one frontier that will be detected from it.

If IFD is combined with a SLAM algorithm based on particle-filters and as a result a new particle is being chosen, map orientation might change. In this case one should recalculate the frontiers by processing the entire image (like any traditional methods mentioned earlier) because we cannot use previous saved frontier information.

We propose to implement IFD and analyze its performence over simulated and real world data obtained from the robot.

3.2 Room/Corridor Detection

Fortunately, labeling maps with semantic labels is possible by several methods that involves lasers [14, 19, 13], vision [16] and even a combination of them [15, 8].

All semantic labeling methods share in common the utilization of a *semantic classifier*. A semantic classifier is a component that analyzes sensor readings and maps for each part of the environment a semantic label. We intend to implement the following heuristics by creating a semantic labeler that is combined from a vision-based classifier and a laser-based classifier.

In the following sections we introduce our proposed work that is based on utilizing a semantic labeler. By this utilization, we intend to speed up the exploration process.

3.2.1 Exploration Scanning Heuristic

A common exploration situation is when a robot enters a room and gets a sensors reading. When integrating the reading into its self built map, the robot finds out that it got a nearly complete scan of the room. Figure 2 shows a robot that has just performed a room scan. It will be inefficient to navigate to the corner because the navigation is not likely to add any new information of the environment. A human can easily understand that the current scanned environment object is a room, deduce that only a single corner is missing and therefore exit the room and navigate to the next target (because navigating to the corner will probably not add such significant new data). A robot that is not aware of its environment will navigate to that frontier, arrive to the corner and then exit the room and navigate to the next target.

We propose to use a semantic labeler and implement the above heuristic. If the robot's current scanned environment part is classified as a room, the robot will navigate to the next target. The idea behind this heuristic is that corridors are more likely to provide new topological information rather than room (which is probably not connected to any other rooms, except the corridor). We intend to test this heuristic both in simulation and real world data.

3.2.2 Exploration Priority Heuristic

By many state of the arts exploration methods, the next target of the exploring robot is chosen by geometric features of the environment [19]. However, the

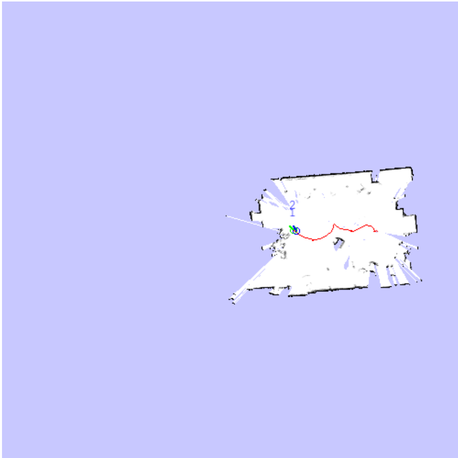

Figure 2: Bad Navigation Example

room contents are not taken into account when deciding about the room classification. For example: a lab and a kitchen can have almost same geometric features, but they are differed by the objects that are located in those rooms (i.e. computers, desks, refrigerator, coffee machine etc.). By enabling the exploring robot the ability to distinguish different types of rooms, we can prioritize the exploration targets. For instance: in a military operation we are likely to prefer exploring weapon workshops rather than kitchens.

We propose to use a vision labeler and implement the above heuristic. After the labeler has determined current room's type, the next target will be determined according to the priority of the type. We intend to build a dynamic system that gets a priority set and navigates according to it. We build on the work of [17] and propose the following weight function of targets:

$$W(x) = p(x) \cdot \frac{v(x)}{t(x)}$$

x stands for a frontier cell. $W(x)$ stands for the weight function. $p(x)$ stands for the priority of the given cell x. $v(x)$ and $t(x)$ represents the value and time which are obtained by reaching target x accordingly.

We claim that the above weight function represents better the reality. We intend to test this heuristic both in simulation and real world data.

3.2.3 Reduce Interruptions to the Operator

An important and common task of exploring robot is to record videos of the environment, in more praticular, to record a video for each new location (i.e. room) that is being revealed. In current exploration methods, the robot is not aware of its environment and therefore needs to interrupt the operator. The operator then manually drives the robot to a location where it records a video. In the end of this process, the robot continues in its exploration process and so on. In order to minimize interruptions to the operator as much as possible, the robot should perform this common task by itself (i.e. no interrupt the operator).

We propose to create a mechanism that analyzes whether the robot enters a room, determines where is the best location to record the video without interrupting the operator. In order to implement the above heuristic, we are going to base on a semantic labeler. Rooms that are classified with the same type are likely to have common geometric structure. Thus, the robot is likely to record those rooms from the same location. The result is less interruptions to the operator. Therefore, we attend to use machine learning techniques in order to learn the best location for recording of each type.

4 Work Plan

We propose to solve the problems that are mentioned above. We'll do so by:

1. implementing IFD (Algorithm 2)
2. implementing a mechanism that enables the robot to use semantic information and speeds up the exploration time (section 3.2.1)
3. implementing a mechanism that enables receiving a priority set of scanning types and determine the targets to be explored.
4. implementing a mechanism that records videos from rooms without interrupting the operator. This mechanism will enable to build a topological map of the environment. Each node will contain the video that was taken by the robot (3.2.3)

We will test and experiment the value of each contribution of all the above algorithms and mechanisms. We will examine the exploration speed up that is gained by each of the proposed algorithms and mechanisms separately and all together.

To carry out all steps, we will use the NAO robots in the MAVERICK research lab.

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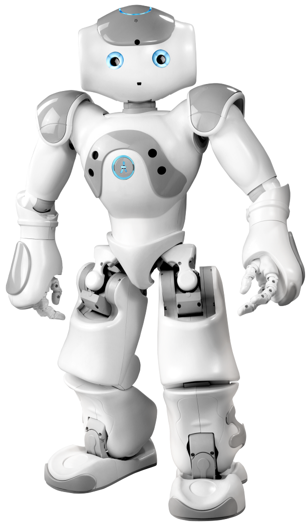

Figure 3: NAO robot

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