Using Contacts During Robot Manipulation to Map and Reconstruct a Scene

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Abstract—**Robot grasping and manipulation in real world scenarios typically imply *i)* objects of unknown shape, *ii)* cluttered, unstructured settings with a high degree of uncertainty, and *iii)* contacts between the grasped object and obstacles in the environment. In this paper we present an approach to reconstruct the shape of a grasped object and map the environment by measuring the contact forces while a robot tries to retrieve an object from a scene. We use a probabilistic approach that computes the probability of occupancy of two 3 dimensional maps (one for the grasped object and one for the environment), where the update on each map informs the construction of the other. Our method relies only on the force and torque measurements from the robot end-effector to find the line of action of the interaction forces, compute the possible contact locations and populate the two occupancy maps. Here we present our method, that we named SMORE (Simultaneous Mapping and Object Reconstruction), and discuss some future developments of this approach.**

I. INTRODUCTION

When robots operate outside laboratories and factories, in scenarios such as our homes or the outdoors, there is an inherent uncertainty that comes with being in these unstructured environments. This uncertainty brings about a number of difficulties and challenges when a robot has to grasp and manipulate objects. In these tasks, there is typically limited *a priori* knowledge on object properties, such as its friction, mass, and even its shape, as well as the shape of the environment (map). Then, as the robot interacts with the world, there is a high chance of unexpected collisions between robot and environment or between the grasped object and the environment. It is also important to note that in some scenarios the usage of computer vision may be limited, particularly when there is a significant amount of clutter and disarray. In these situations, other sensing modalities such as tactile and force sensing can be useful to obtain information relevant to the task.

Here we detail a method that uses the force measurements when a grasped object collides with obstacles in the environment while trying to retrieve it, to simultaneously reconstruct the shape of the object and the obstacles in the environment. This method populates two 3D maps with the probability that the voxels are occupied and, as we learn more about one of the maps (object or environment), so it becomes easier to construct the other. We devised two probability laws to update the maps: one is applied when a contact is detected, the possible contact locations are computed and the voxels along that line are updated; the second probability law is applied when
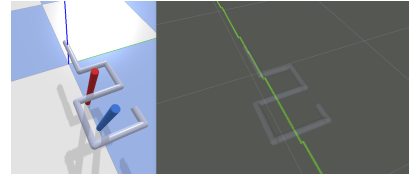
(a) Discretization along the force line-of-action $\mathcal{L}$
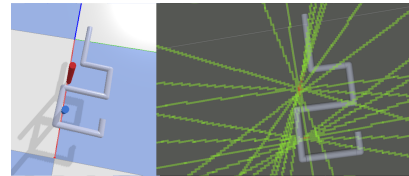
(b) Obstacles are detected after a number of contacts

Fig. 1. Simulated environment: S-shaped object and two vertical peg obstacles. (a) Collisions between the object and an obstacle generate a force, and its line-of-action can be computed. (b) As multiple collisions occur along different line-of-actions, we can probabilistically determine the occupancy probability.

there is no force detected, and so the object is not in contact with an obstacle. We consider an application of our method, where an object of unknown, complex shape, is "tangled" with obstacles in the environment. The system repeatedly attempts to retrieve the object by planning a collision-free path with its current knowledge of the object and map geometries. As it fails to retrieve the object and hits the obstacles, the maps are constructed and refined until enough of the object and obstacles is known to achieve a successful retrieval. This method was previously presented in [1], and here we discuss some of the limitations and future possibilities of this work.

II. METHODS

The proposed method builds and populates two 3D maps: $\mathcal{M}_w$ maps the environment and is attached to a fixed frame, and $\mathcal{M}_o$ moves with the robot end-effector describes the shape of the grasped object. The occupancy of each voxel is updated sequentially and taking into account the current probabilities. When a collision is detected, the occupancy probabilities increase for the possible contact locations, while the opposite occurs when the robot is moving in free space without hitting an obstacle.
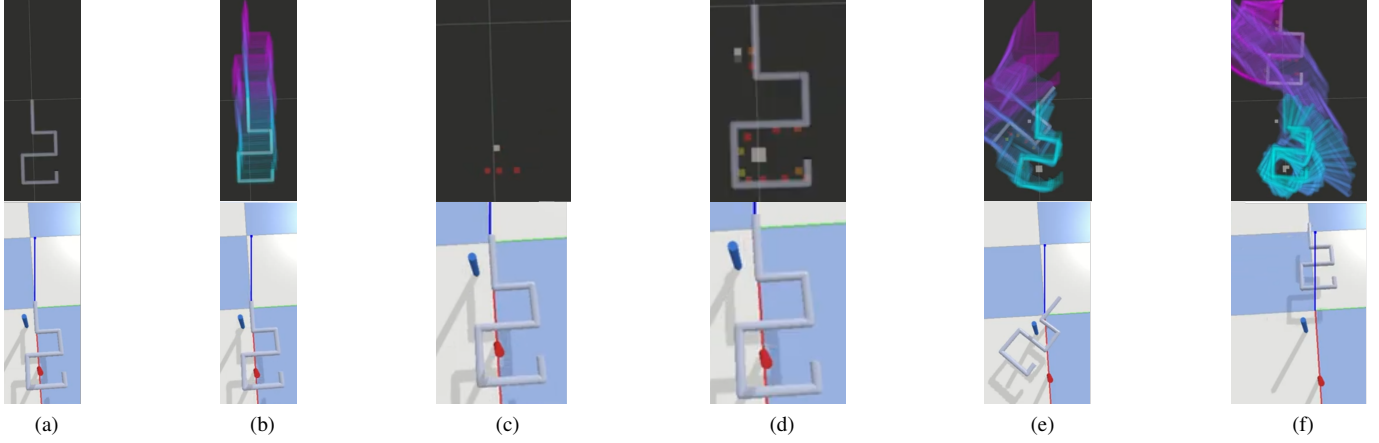
Fig. 2. Object untangling: method to map the environment and reconstruct the grasped object. Top row: Object reconstruction in green/red, mapped obstacles in black/white, planned path in cyan/purple. Only voxels with a probability of occupancy higher than 50% are displayed. Bottom row: Simulation environment.

A. Probability Laws

1) Probability law for contact: When there is a collision between the object and the environment, we first calculate the line of action of that force given the measured force and torque. We can then find the possible contact location as the set of voxels $\mathcal{L} \subset \mathcal{M}$ that are intersected by this line. We update the occupancy probability of occupancy of each voxel $P(O^p), p \in \mathcal{L}$ with the probability law [1]:

$$P(O^p)_{t+1} = \frac{PP' + \left(1 - \dfrac{\Pi}{1 - PP'}\right) \cdot P\overline{P'}}{1 - \Pi} \quad (1)$$

where

$$P = P(O^p) \,, \; \overline{P'} = P(\neg O^{p'})$$

$$\Pi = \prod_{n \in \mathcal{L}}(1 - P(O^n) \cdot P(O^{n'}))$$

2) Probability Law for free space: When there is no contact we can also use that information to update our maps. In these situations there cannot be two coincident voxels that are both occupied, since otherwise there would be a collision and we would measure a force. So, the occupancy probability is decreased for every pair of overlapping voxels according to the law:

$$P(O^p)_{t+1} = \frac{P(O^p) \cdot (1 - P(O^{p'}))}{1 - P(O^p) \cdot P(O^{p'})} \quad (2)$$

which states that the occupancy probability $P(O^p)$ is obtained simply by dividing the cases where p is occupied (and thus p' is free) by the probability of no collision. The converse operation is also applied to p' to obtain $P(O^{p'})_{t+1}$.

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[1] for more details on this derivation see ref. [1]

III. RESULTS

An example is shown in Fig. 1 for the calculation of the force line of action, and the environment map after a number of collisions. The probability that a voxel is occupied is higher at the intersection of these lines. We applied the method in simulation to the problem of removing an object of unknown geometry from a situation where it is tangled in an environment. An RRT planner was used to find collision-free paths given the current knowledge of object and map. Figure 2 shows an execution of the task. At first (2a and 2b), the robot attempts to go in a straight line, after which it collides with the environment several times. At the point shown in 2c, parts of the object and the red peg in the environment have been reconstructed. At point 2d and 2e the scene is almost fully reconstructed but the removal is still unsuccessful until point 2f where the object has been fully reconstructed and the planner is able to devise a path that does not collide with the environment.

IV. DISCUSSION

The proposed method works reasonably well, and outperformed a benchmark c-space planner and a reinforcement learning approach in the previous task. It does suffer, however, from a number of limitations and could benefit from some improvements. The main drawback is the inability to deal with multiple simultaneous contacts. Secondly, the order at which the measurements arrive influences the result. Finally, the method assumes the object is rigidly attached to the end-effector frame, which might not be the case if the forces displace it within the robot hand. In terms of improvements, we are considering the combination of a vision system to provide at least partial information, and to use optimal planners that use occupancy probability, rather than deciding that a state is valid or invalid.

REFERENCES

[1] Joao Bimbo, Andrew S. Morgan, and Aaron M. Dollar. Force-based simultaneous mapping and object reconstruction for robotic manipulation. *IEEE Robotics and Automation Letters*, 7(2):4749–4756, 2022.