

PLANNING STACKING OPERATIONS WITH AN UNKNOWN NUMBER OF OBJECTS

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Abstract: A planning framework is proposed for the task of cleaning a table and stack an unknown number of objects of different size on a tray. We propose to divide this problem in two, and combine two different planning algorithms. One, plan hand motions in the Euclidean space to be able to move the hand in a noisy scenario using a novel Time-of-Flight camera (ToF) to perform the perception of the environment. The other one, chooses the strategy to effectively clean the table, considering the symbolic position of the objects, and also its size for stacking considerations. Our formulation does not use information about the number of objects available, and thus is general in this sense. Also, it can deal with different object sizes, planning adequately to stack them. The special definition of the possible actions allows a simple and elegant way of characterizing the problem, and is one of the key ingredients of the proposed solution. Some experiments are provided in simulated and real scenarios that validate our approach.

1 INTRODUCTION

Algorithms for planning explicitly considering uncertainty have been widely used in the field of mobile robots (LaValle, 2004; Thrun et al., 2005), but are less common in robotic-arm manipulation and grasping (Hsiao et al., 2007). In that scenario uncertainty is especially important and should be carefully considered because contact takes place between the robot and the world. In this interaction, the position of the object and the robot in the world cannot be precisely known, even more if we consider uncertainty in sensors we use to sense this world.

In this paper we want to explore object grasping and stacking tasks, as they are interesting and challenging skills (Kemp et al., 2007). In order to deal with these problems the *partially observable Markov decision process* paradigm will be used, specifically the *discrete model based POMDP*. It provides the capacity of dealing with uncertainty in observations and actions, usually a robot will have an approximation of reality when is sensing the environment and evaluating the results of the actions completed. POMDP have been used before in the context arm motion control for grasping, however perceptions used are simpler than here, i.e. on/off signals from pressure sensors on the fingers of the hand (Glashan et al., 2007).

The system uncertainty is modeled by measuring



Figure 1: The robotic arm used in the experiments executing the policy computed by the planner.

it in the real system and providing the values to the system, so it can take into account the various difficult situations it could face according to the chosen action. One interesting characteristic of our approach is that two different POMDPs are combined and one of them can control the other one and get feedback from it. We will apply this approach to solve a real situation: to clean a table and stack an unknown number of objects of different size on a tray.

The first POMDP will control robotic arm trajectory to prepare the grasping task, planning in the *space state* formed by the relative coordinates to the target state. This approach is extensively reported in (Trilla, 2009). Here will be briefly introduced. A

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naive approach to avoid the POMDP complex mechanism is a simple reactive algorithm. However, within this approach is difficult to take into account the uncertainty in the number of stacked objects and the probability of stacks falling down.

The second POMDP will plan symbolically the strategy of the cleaning task and the actions chosen for the target of the first POMDP. The objective of the second POMDP is either to completely clean the table or fill the tray. The planification is symbolic because it does not rely on the coordinates of the objects or its interaction with the world, but on an abstraction layer. Two main considerations are important. First, observations are partial: the number of objects on the table is unknown, i.e. because of possible occlusions, and some objects maybe are pre-stacked on the table and this is difficult to observe. Second, the tray surface is limited so it has to stack objects. Here the planning has to deal with objects of different size.

Perception in grasping applications is generally performed using artificial vision to recognize some object characteristics, and then plan a correct grasp (Saxena et al., 2008). Here we will use a relatively new sensor, a ToF (Time of Flight) camera. This camera delivers 3D images at 25fps, potentially allowing fast perception algorithms and, contrarily to stereo systems, it does not rely on computing depth on texture or other object surface characteristics. Depth information will be used to identify the position of the robot hand in the space, and to easily separate objects from background.

This article is structured as follows. POMDP background is introduced in Section 2. The planification strategy is introduced in Section 3, and in particular the planification of the symbolic steps that are involved in the container-content manipulation (Section 3.1). In Section 4 some experiments are presented, validating our approach in a general stacking case, in the case of different object sizes, and with occlusions between objects. Finally, Section 5 is devoted to the conclusions and future work.

2 POMDP BACKGROUND

A POMDP models a sequence of events in discrete states and time where the agent chooses actions to perform. It is represented by the tuple (S, A, T, R, O) where S is the finite set of *states* and A is a discrete set of *actions*. The *transition model* $T(s, a, s')$ describes the probability of a transition from a state s to s' when the action a is performed. The *reward model* $R(s, a)$ defines the numeric reward given to the agent when it executes an action a being in state s . *Observation*

model $O(z, a, s)$ describes the probability of an observation z when the action a is performed, and the state is s . A POMDP handles partially observable environments, there is only an indirect representation of the state of the world. The *belief state* b is the probability distribution over all states in the model. At each time step the belief state is updated by Bayesian forward-filtering.

A decision about which action is most applicable is given by the policy function which contains the information about the best action to perform for any possible belief distribution. The policy balances the probabilities of a future sequence of events with the expected accumulated reward which has to maximize. Computing a policy is highly intractable with classic exact methods like *value iteration* or *policy iteration*. However, some recent work has been devoted to find approximated solutions (Hsu et al., 2007), as *point based value iteration* (Hsu et al., 2008), *discrete Perseus* or HSVI are quite fast and yield good results.

3 PLANNING AND EXECUTING THE MANIPULATION OPERATIONS

We divide the high level task of cleaning a table of several objects in two different levels. First, it is important to decide which object to first manipulate. Then, the next issue is to know the exact position of the object and effectively manipulate it. Here we will present our development for the planning algorithm which deals symbolically with the problem and performs high level task.

The effective manipulation of the objects can be solved by means of a classical control algorithms. Alternatively, we have recently proposed to solve the low level task defining also a POMDP in the space of discretized hand positions (Trilla, 2009). With this approach we are able to deal with robots with low precision or repeatability, and also with mobile robot manipulators that naturally are not exactly placed equally in front of a table.

3.1 Planning the Strategy

We define the problem as follows. The working area is divided in zones: one for the tray and the rest for the table (see Fig 2). Each zone is divided in positions where the objects can be placed. Space state is defined as the set (z, p, sn, t) , where z (*zone*) and p (*position*) identify the object location symbolically, sn indicates the number of objects stacked in the same

purely by noise in the observations. Second, the solution to the problem implies stacking objects of different size with some restrictions, i.e. a big object cannot be stacked onto a small one.

Thanks to the proposed space state and action space, the codification of the different positions and sizes of the glasses lets the planner generate a policy able to deal with the container-contents problem stacking the glasses in the best way, maximizing the free space on the tray. The solution we propose to be able to handle the unknown number of objects is based on focus the attention on only one of the objects present in the each one of the different regions on the table, and it has turned out to be particularly adequate and powerful.

5.1 Future Work

Here we have considered that the objects can be already stacked on the table, and that the the robot can perform stacking actions on the table. However this condition has hardly raised in our experiments. One challenge we are facing now is to incentive object stacking actions on the table, before putting them in the tray. A new variable is needed here to balance the cost between two transportation actions and one stacking plus a transportation operation. In the computation of this cost the trajectory from the table to the tray in the transportation action becomes important, as we want to stack closer objects, or more important, stack objects that are in the transportation trajectory to the tray. Our formulation is general in the number defined zones on the table, so we face this new condition as a natural extent of the presented algorithm.

We have considered to add an additional action when observations are not enough to decide for one action, i.e. in order to gather information about the number of glasses stacked on each position. A promising option is an asking action to an operator where the answer could modify the agent's belief state (Armstrong-Crews and Veloso, 2007).

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