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Axiomatic Particle Filtering for Goal-directed Robotic Manipulation

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Abstract— **Manipulation tasks involving sequential pick-and-place actions in human environments remains an open problem for robotics. Central to this problem is the inability for robots to perceive in cluttered environments, where objects are physically touching, stacked, or occluded from the view. Such physical interactions currently prevent robots from distinguishing individual objects such that goal-directed reasoning over sequences of pick-and-place actions can be performed. Addressing this problem, we introduce the Axiomatic Particle Filter (APF) as a method for axiomatic state estimation to simultaneously perceive objects in clutter and perform sequential reasoning for manipulation. The APF estimates state as a scene graph, consisting of symbolic spatial relations between objects in the robot's world. Assuming known object geometries, the APF is able to infer a distribution over possible scene graphs of the robot's world and produce the maximally likely state estimate of each object's pose and spatial relationships between objects. We present experimental results using the APF to infer scene graphs from depth images of scenes with objects that are touching, stacked, and occluded.**

I. INTRODUCTION

In order for autonomous robots to interact fluidly with human partners, a robot must be able to interpret scenes in the context of a human's model of the world. The challenge is that many aspects of the human's world model are difficult or impossible for the robot to sense directly. We posit the critical missing component is the grounding of symbols that conceptually tie together low-level perception and high-level reasoning for extended goal-directed autonomy. We specifically face the problem of anchoring [4], a case of symbol grounding [7], to associate physical objects in the real world and relationships between these objects with computationally assertable facts (or axioms), from the robot's perception of the world. With a working memory of grounded axioms about the world, robot manipulators will be able to flexibly and autonomously perform goal-directed tasks that require reasoning over sequential actions (illustrated in Figure 1). Just as important, human users will be able to more intuitively specify goals for robots, as desired states of the world, through spatial arrangements, such as the scene graph representation that is now ubiquitous in modern 3D computer graphics.

Toward this end, we aim to estimate axiomatic representations of the world that allow robots to build on the body of work in sequential planning algorithms, which have over a five-decade history. Described in early work, such as STRIPS [6] and SHRDLU [21], classical planning algorithms adapted theorem-provers to "prove" conclusions about goals based on axioms that describe the world. A classical planner can compute actions for a physical robot to perform arbitrary sequential tasks assuming full perception of the environment, which is an unrealistic assumption. The real world that robot attempts to perceive is dominated by uncertainty in the robot's sensing and action. This uncertainty affects both the robot's axiomatic representation of that world and its ability to perform effectively.

While domains with uncertainty are traditionally problematic for classical planning, we posit that advances in robot perception and manipulation with new approaches to anchoring can overcome this uncertainty for effective robot control. Uncertainty is a result of both measurement by the sensors and performance by the motors that control the robot. For example, sensor measurements are frequently not adequate for segmentation of objects in contact, or identification of occluded or partially visible objects (Figure 2). The resulting noisy and incomplete descriptions of a state are unsuitable inputs for existing planning algorithms.

Generative models provide a means to address uncertainty probabilistically. Instead of trying to discriminate the state of the world from uncertain sensory observations, possible world states can be hypothesized to explain possibilities for the true world state that could have generated the robot's observations. These generated hypotheses form an approximate probability distribution (or belief) over possible states of the world. Avoiding the intractability of planning in the space of this belief, a state estimate from the resulting belief distribution is taken to represent the current state of the world for classical planning. This use of the state estimate for planning emulates the ubiquitous approach to autonomous navigation for planning from localization state estimates.

In this paper, we propose an approach to axiomatic state estimation, the *Axiomatic Particle Filter (APF)*, to perform anchoring and manipulation in cluttered scenes containing objects in physical contact. We describe the problem of axiomatic state estimation as the perception of a robot's environment axiomatically as a scene graph, where each object in the scene is a node and inter-object relations are edges. For autonomous reasoning over sequential tasks, we discuss how axiomatic state estimates can provide both the computational tractability of classical planning and robustness of probabilistic inference for perceptual uncertainty. The Axiomatic Particle Filter is then presented as an implementation that estimates the pose and spatial relations of objects in a scene from 3D point clouds, assuming known object geometries. We present experimental results of APF along with a sequential manipulation for controlled scenes

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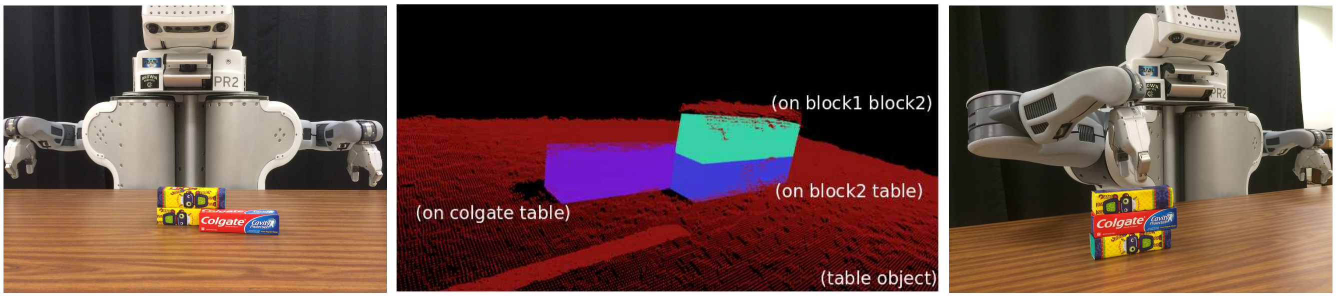


Fig. 1: The Axiomatic Particle Filter in a "Tower of Colgate" example. The APF estimates the state of a scene with occlusions and touching objects (left) as axioms for individual objects and their inter-object relationships (middle). This state estimate is then used by a planner to achieve the goal state (right), the insertion of the toothpaste box between the two blocks.

involving objects that are physically touching, stacked, and partially occluded.

II. Related Work

The APF addresses the same problem as Rosman and Ramamoorthy [17] for estimating the scene graph of an environment, as a collection of axioms representing objects with pose and geometry, and inter-object relations. Their work asserts knowledge of basic contact physics in their interpretation of point clouds into scene graphs. The approach works well assuming the shapes of the structures and their configurations have discriminable contact points. In contrast, the APF does not rely upon such feature extraction and discrimination. However, in its current implementation, the APF uses a limited set of relations and requires known object geometries for tractability.

In the KnowRob system of Tenorth and Beetz [19], sequential planning for manipulation in household tasks is performed on symbolic data representations based on the semantic web. KnowRob accommodates uncertainty at the symbolic level, such as the selection of subgoals. However, it relies upon hard state estimates about the poses of and relations between objects. These estimates, as well as low-level motion planning, were provided by hardcoded software components in the Robot Operating System (ROS) [16]. Srivastava et al. [18] perform joint task and motion planning. This work also does not consider perceptual uncertainty in relying on hardcoded perception systems that take advantage of modifications in controlled environments (e.g., "green screening", augmented reality tags).

Closest in spirit and approach to the APF is the work by Mohan et al. [12], [9] for goal-directed control of a robot arm using the Soar cognitive architecture. Soar's Spatial Visual System constructs a scene graph of the environment, equivalent to the axiomatic representation in this paper, given low-level probabilistic perception of solid-colored objects. Soar is then able to reason over actions, in the face of occlusions, for the robot to play games such as Tic-tac-toe and Connect-4. Chao et al. [2] take a similar approach to goal-directed robot learning from demonstration. In contrast to these projects, the APF maintains a distribution over all possible scene graphs, and not reliant upon selecting and maintaining a hard (potentially incorrect) state estimate for perception. Similar to particle filtering for robot localization, the APF could be used to complement these methods and extend to broader collections of robot systems.

It is tempting to characterize the problem of planning under uncertainty as a POMDP [8]. The state of the world is only partially observable in the POMDP formulation, and the process of a robot making a decision and then acting is formed as a Markov process over the space of all possible world states. POMDPs have proven computationally infeasible for all but a small number of discrete-state problems. For robotic manipulation, Lang et al. [10] attempt to overcome the limitations of the POMDP through online relational reinforcement learning, using physical simulation for exploration.

Other groups are looking at using particle filtering to combine the symbolic and statistical approaches [5], [22]. Our contribution is to bring similar methods into a more practical realm, and to provide a more faithful grounding of relational particle filtering with an embodied robot system.

III. Axiomatic State Estimation

To motivate the problem, consider the scene in Figure 3. For this scene, assume the goal for the robot is to grab the bottom yellow block and give it to a human user. It can be clearly observed that *block1* (the top block) and *block2* (the bottom block) are two distinct objects from the perspective of human perception. A naïve perception of this scene, common to most robots, would instead perceive objects that are physically touching as a single object. From the perspective of common segmentation methods for 3D point clouds, the belief that these objects are a single object is an equally likely parsing of the scene.

To capture this uncertainty, we need to maintain a distribution across plausible scene graphs supported by the point cloud observations. This ambiguity can be resolved at a later time with further information, such as after a robot action to grasp one of the objects. In addition, the robot can use either one of these hypotheses as an estimate of the scene state to plan and execute a current course of action. If the chosen state estimate was incorrect, the alternate hypothesis of the scene should still be represented in the belief distribution. Assuming the result of the action resolved the ambiguity, this alternate state hypothesis will now have a greater likelihood

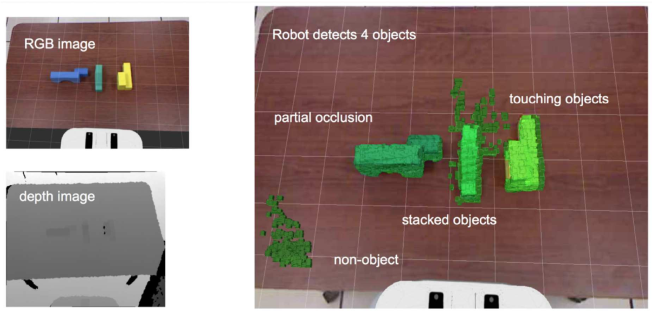


Fig. 2: Issues with object segmentation using the PR2 Interactive Manipulation [3]. Due to issues of uncertainty in open-loop perception, reliable autonomous robot manipulation is currently limited to distinctly separated objects on flat tabletops. For example, consider the scene of 6 simple blocks on a tabletop and its depth image from a Kinect RGBD camera on the head of a PR2 robot. The robot can find the tabletop, assuming it is the largest flat object in the scene. However, it cannot distinguish (and thus grasp directly) any of the individual objects due to occlusions, physical interaction, and false positives.

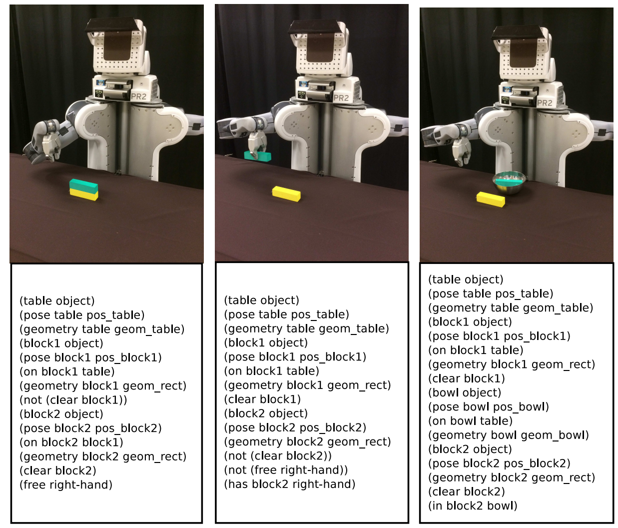


Fig. 3: Examples of axiomatic state for: (left) two blocks stacked on one another, (middle) one of those blocks possessed by the robot, and (right) this block placed into a bowl that just happened to appear unexpectedly.

given the new point cloud observation. This distribution will now clearly distinguish the alternate as the true scene state estimate from which the robot's plan can be recomputed.

A. Model

We model this problem of axiomatic state estimation as a recursive Bayesian filter, a common model for state estimation in robotics [20]. The sequential Bayesian filter is described by the following equation, with x_t being axiomatic state x at time t, sensory observations z_t, control actions u_t taken by the robot, and x_G to be a given axiomatic goal state:

$$p(x_t|z_{1:t}) \propto p(z_t|x_t) \int p(x_t|x_{t-1},u_{t-1}) p(x_{t-1}|z_{1:t-1}) \mathrm{d}x_{t-1} \quad (1)$$

Axiomatic state x_t is the collection of axioms used to define a possible world scene graph for the pose and geometry of each objects and inter-object relations. In the general case, axiomatic state estimation would infer the collection of axioms and parameters for each axiom. This general case can lead to a very high dimensional belief space that would theoretically pose problems for probabilistic inference. In the following section, we demonstrate how axiomatic state can be performed within reasonable computational and conceptual constraints for scenes that are problematic for many current methods.

The Planning Domain Definition Language (PDDL) [11] is used to model axiomatic state as a formal language, which implicitly defines a scene graph. Figure 3 shows three example scenes defined axiomatically in PDDL. These axioms include *(X object)* to assert that object X exists in the scene, *(geometry X V)* to assert X has spatial geometry V (as a pointer to a geometric mesh represented in the objects local coordinates), and *(pose X Q)* to assert X has spatial pose configuration Q (with respect to the frame of its parent in the scene graph).

We restrict axioms to be only spatial and physical in nature, such that they can be evaluated by collision detection, physical simulation, and robot proprioceptive systems. As such, our inter-object axioms assert relations only about whether *(in X Y)* an object X is inside another object Y, *(on X Y)* resting or physically supported by another object Y, or *(has X R)* in the possession of a robot R. Each of these axioms establish that the object X is the child of another object (or robot) in the scene graph. Additional axioms can maintain assertions about whether the robot has a free manipulation endeffector resource and whether an object has a free support surface for the placing another object.

B. Axiomatic Particle Filtering

At each moment in time, an axiomatic state estimator will maintain a belief $p(x_t|z_{1:t})$ about the state of the world x_t informed by the robot's sensor observations z_t. In APF, this belief is maintained as a collection of particle hypotheses, with each particle hypothesis being a collection of axioms describing a possible state of the world. Given the action taken by the robot u_{t-1} and its prior belief $p(x_{t-1}|z_{1:t-1})$, the APF makes a prediction about the distribution of belief at the current time t by updating and resampling the set of particle hypotheses based on a given dynamics prior $p(x_t|x_{t-1},u_{t-1})$. Particle hypotheses from this predicted belief are then evaluated against sensory observations z_t by a likelihood function $p(z_t|x_t)$. The result is the posterior distribution $p(x_t|z_{1:t})$ representing the distribution of belief for the current state of the world at time t. From this distribution, a single hypothesis is selected as an estimate $\hat{x}_t$ of the actual state of the world, often as the maximally likely particle hypothesis. The APF will then give this state estimate $\hat{x}_t$, as a collection of axioms, to a classical planner to generate the next action u_t towards reaching a goal state x_G, also specified as a collection of axioms.

Within this model of axiomatic state estimation, there are

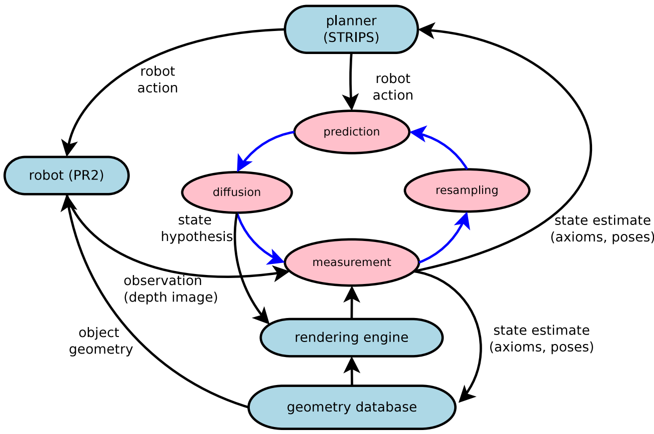


Fig. 4: System Architecture for sequential manipulation, with Axiomatic Particle Filter components highlighted,

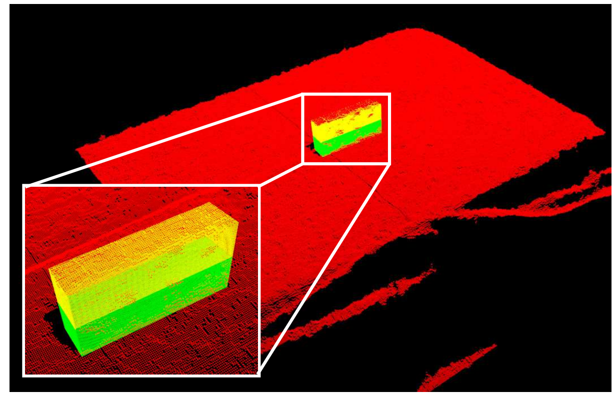


Fig. 5: Known geometries for the two stacked blocks example (yellow on green and green on a table) shown on the observed point cloud data.

a number of broader challenges, which include: prediction of future states through the dynamics potential, evaluation of states with respect to observations in the likelihood function, and generating a computationally tractable and accurately convergent symbol grounding for the planner.

IV. Implementation

In this section, we discuss at greater depth our implementation (Figure 4) demonstrating sequential goal-directed manipulation system using APF. The core of this implementation is our APF modules for performing state estimation through *prediction*, *diffusion*, *measurement* and *resampling*. In APF, the distribution over states is represented as a mixture model of particles, each representing an axiomatic state. For computational tractability, we assume object geometries are known and the object pose consists of two-dimensional position with respect to the parent object frame. We further assume that invalid samples, where a child object is outside the support surface of its parent, can be evaluated and disregarded through resampling. In actuality, object poses are conditionally dependent upon inter-object relations and object geometry, which will be a subject of future work.

As shown in Figure 4, the *measurement* module gets the observation from the robot and hypothesized particles generated from the rendering engine. Robot observations are in the form of depth images from a Microsoft Kinect mounted on the head of a Willow Garage PR2 robot. The likelihood of a particle is calculated by comparing the depth images of the observation and a graphical rendering of the axiomatic state hypothesized by a particle. The comparison function is a sliding window sum of squared distance (SSD) on two images. The z-buffer of an OpenGL-based graphics rendering engine is used to generate depth images from axiomatic states. We assume a known intrinsic calibration and extrinsic pose for the Kinect camera and that all the object geometries are known and stored in a geometry database. Figure 5 shows the point cloud both from Kinect and the rendering engine for a particular axiom overlayed on each other. This figure shows how well the rendering engine is able to generate depth images corresponding to a given axiomatic state.

Result of the *measurement* module is the posterior distribution representing the distribution of belief for the current state of the world. If the particles converge within a threshold, the *planner* takes the maximum likely state estimate and computes a plan of action for the robot to execute. In parallel, the *resampling* module takes in the posterior distribution and performs importance sampling over their states to give the new distribution of particles to the *prediction* module. Based on the robot action decided by the *planner*, the *predict* module updates the state of the particles. The *diffusion* module adds noise randomly to this distribution of particles and *measurement* is performed again with a new observation from the robot. The *diffusion* module also updates the rendering engine with new set of axiomatic states to generate particles.

A STRIPS-based planner [6] with A-star implementation is used for sequential planning in our manipulation system. With goal and the current state of the world, the *planner* would compute a sequence of actions towards the goal and output the next immediate action to the robot. Actions from the planner will be pick-and-place actions for a specific object in the scene. Given this object's pose and geometry, from the *geometry database*, PR2 Tabletop Manipulation [3] is used to execute these manipulation actions. For the current implementation, replanning does not occur once a state estimate is taken from the converged APF.

V. Results

We conducted two sets of experiments to demonstrate our manipulation system. In our baseline experiment, we evaluated the manipulation system in a scenario of two blocks in different positions representing clutter: non-touching, stacked, and partially occluded. We then considered a more complex scenario of three stacked blocks that need to be rearranged in an arbitrary order from different cluttered starting conditions.

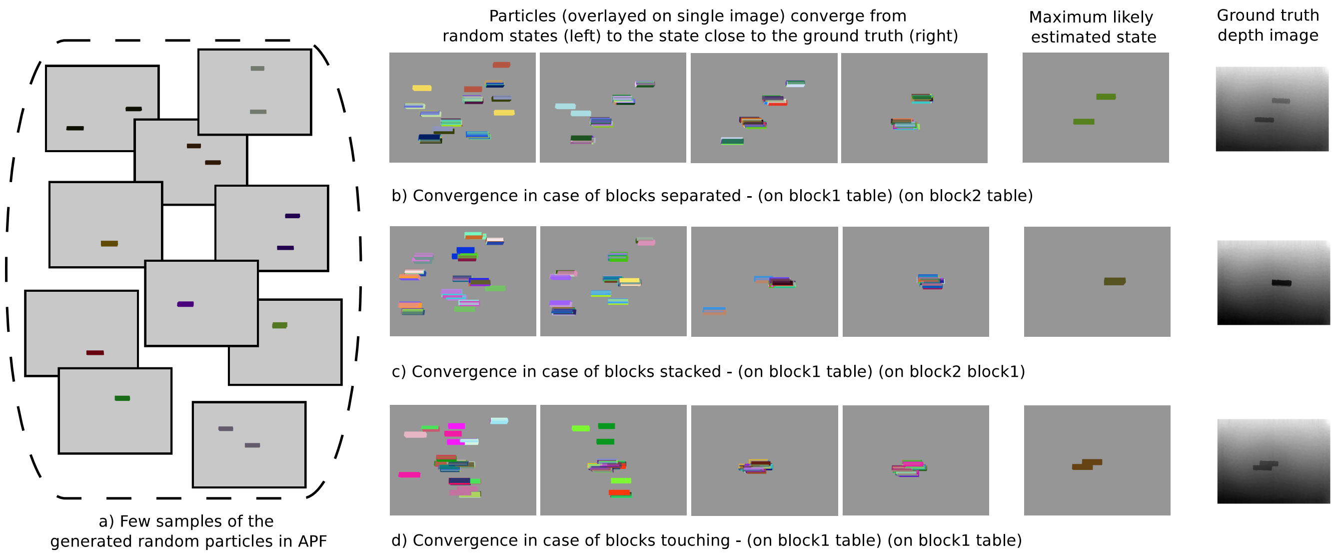


Fig. 6: Convergence of particles from the initial randomly generated states to the estimated state

A. *Two stacked blocks baseline*

In this experiment, we tested the APF system on three different observations representing different spatial relationships (Figure 6) and their convergence. In the initialization, the system will uniformly generate possible scene graphs and positions of objects. Figure 6a shows a few samples of the generated particles in initialization and in this experiment, the system generate 100 particles to track possible world states. Figures 6b-d show the convergence in different scene graph cases for “separated”, “stacked”, and “partially occluded”, respectively. Note that Figure 6d is a special case of Figure 6b which they have the same axioms while two blocks in Figure 6d are touching with each other. The far right panels show the maximum likely estimated state to contrast with the ground truth observation. With our implementation and constant object orientation, convergence typically occurs within 10 iterations.

For the “stacked” condition, the PR2 robot was given the goal to reverse the stacking order of the perceived blocks (Figure 7). The goal of this task is to make the robot perform actions that change the configuration of the blocks from initial state (green on top of yellow block) to goal state (yellow on top of green block). It must be noted that the robot does not have access to the color of the blocks, but only the non-RGB depth image. The use of color for these blocks is only for the purpose of visibility and clarity.

Once the particle filter converges, the estimator results in the centroid positions of the blocks. With the known geometry of these blocks, these centroids are converted to 3D `ROS tf` transforms in world coordinates for input to the robot’s manipulation stack. Figure 5 shows the geometries of the blocks projected onto the point cloud of the scene generated from the depth map. This image shows that the estimator is able to converge to a state that has one block stacked over the other, which is close to the ground truth state of the blocks. This convergence is also shown in the Figure 6.

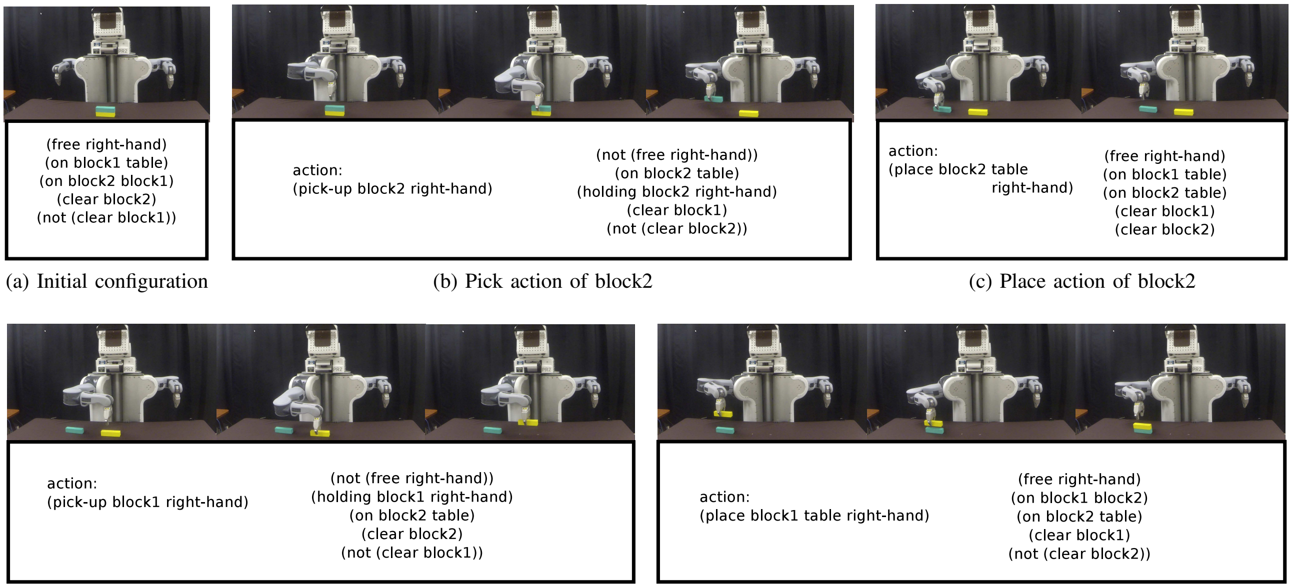
From this state estimate, the planner is given the initial and goal state of the blocks and it returns the sequence of actions. As shown in Figure , this plan involves changing the state from Figure 7a to the last figure of Figure 7b, by doing a pick up action. Once the top object is picked by the robot, a place action is performed which is shown in Figure 7c. This frees the bottom object for pickup which is shown in Figure 7d. Placing the yellow block on the green block would complete the task assigned to the robot, hence a place action is performed as shown in the Figure 7e.

B. *Manipulating three stacked objects*

To explore a more complex manipulation task, another object was added to the baseline scene, a box of Colgate toothpaste. This box has roughly the same geometry as our existing blocks, but a vastly different appearance and texture. The goal for the robot was to build *The Tower of Colgate* by stacking the three objects in an arbitrary order, given by a user, from an arbitrary initial configuration.

The first condition examined was starting from an initial condition where all three objects stacked on top of each other. Shown in Figure 8, the APF is able to estimate the scene graph of this stacking configuration. With this state estimate, the robot can plan and execute actions that will reconfigure the *Tower of Colgate* in any arbitrary order, such as putting the toothpaste box on top. It needs to be noted that the objects are not specifically recognized with an identifier, such as *block1* or *colgate*. Instead, each object is identified only with respect to its configuration in the scene, i.e., its order in the stack.

An even more compelling case is shown in Figure 1 and expounded upon in Figure 9. In this scenario, the clutter scene faces several potential points of failure simultaneously: stacking, partial occlusion, and touching contact. The APF



(a) Initial configuration (b) Pick action of block2 (c) Place action of block2

(d) Pick action of block1 (e) Place action of block1

Fig. 7: Sequence of the actions and states during the task execution by the robot

is able to handle this initial condition well, yielding as state estimate suitable for planning and achieving the desired order for the *Tower of Colgate*. The link to the video is provided here[1].

VI. Conclusion and Future Work

In this paper, we have developed an APF system bringing together axiomatic state that describes the world and the particle filter to estimate the state. Each hypothesized particle represents a scene graph and APF can get the maximum likely particle as the current state for planners to compute actions towards goal. We also used OpenGL rendering engine to render depth image from hypothesized particle with known geometry and compare it with the depth image from robot sensor which acts as an observation. We have shown how the proposed method can be used to estimate the state of the environment and perform sequential manipulation in cluttered environments.

Though our approach to grounding human-robot interaction axiomatically has distinct potential, there are some immediately foreseeable technical challenges. First among them is the high dimensionality of the belief space in which axiomatic beliefs exist. Each potential object or action that could be available to a robot adds dimensions to the belief space. In an unstructured world with no limit on object and actions, this expansion of dimensionality translates into a very large number of particles, and therefore an infeasible computational burden, needed to approximate the distribution of robot states. Finding ways to reduce the dimensionality of the space will be essential to the success of our approach. For example, Boyen and Koller [1] offer a principled method of approaching this problem through factoring the axiom set, and Nitti et al. [15], [14], have suggested ways to implement these methods in the context of a particle filter. Ng et al. [13] suggest a method of sampling particle filters in a manner that accommodates the factoring of the axiom set.

We currently limit objects to rectangular blocks without orientation. A next obvious extension would be to model objects common to human household environments. Modeling household objects will require special scanning systems for offline modeling or human-assisted interactive systems for modeling directly from a robot‘s visual sensors. In addition to bootstrapping the APF, estimation with complete object geometries will be needed for robust object placement actions during manipulation.

[1] https://youtu.be/8LFghHtEIAI

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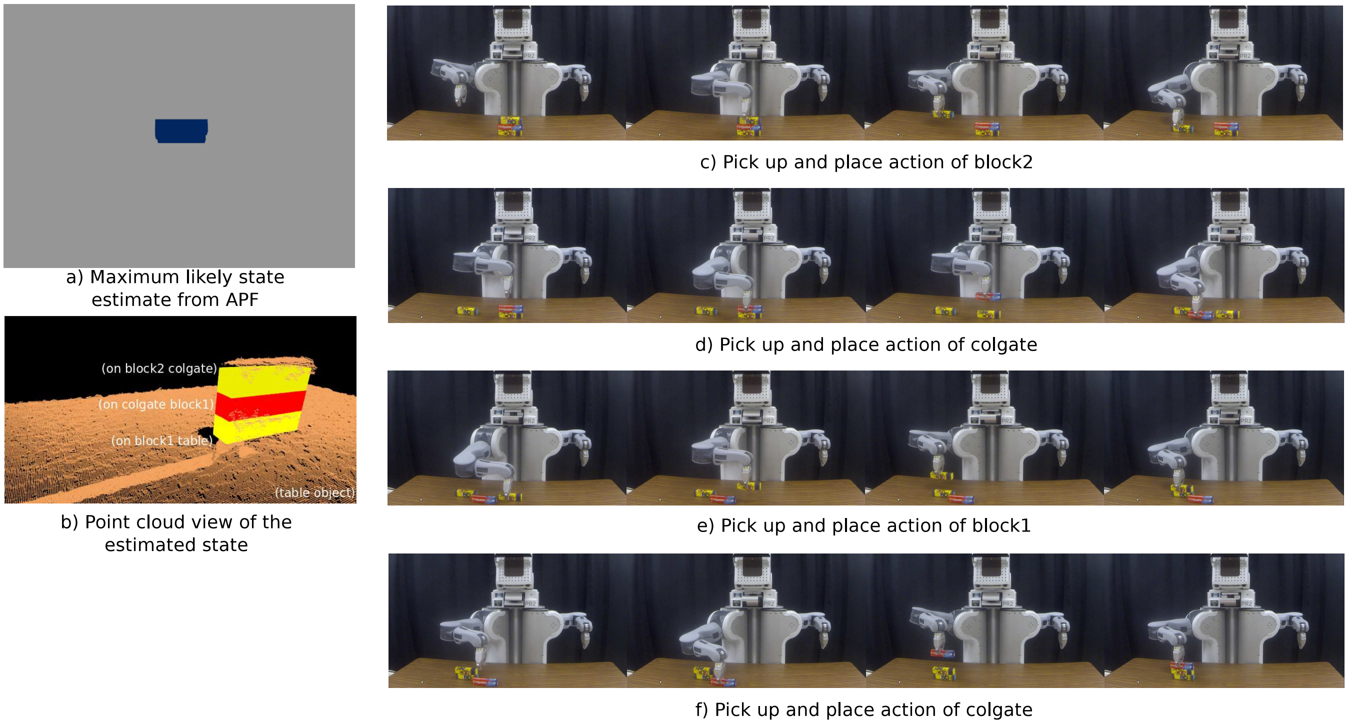


a) Maximum likely state estimate from APF

b) Point cloud view of the estimated state

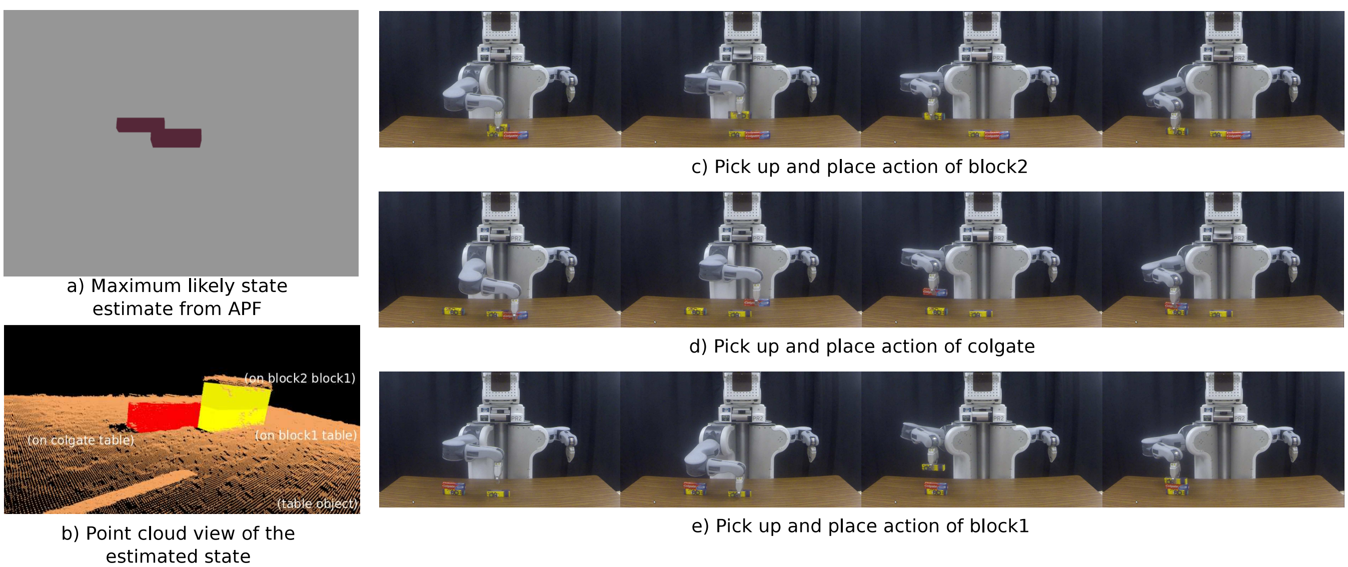
c) Pick up and place action of block2

d) Pick up and place action of colgate

e) Pick up and place action of block1

f) Pick up and place action of colgate

Fig. 8: Estimated axiomatic state from APF along with its point cloud view (left). Frames of robot performing the task of stacking is shown (right) from initial stacked configuration to arbitrary *Tower of Colgate* goal configuration.



a) Maximum likely state estimate from APF

b) Point cloud view of the estimated state

c) Pick up and place action of block2

d) Pick up and place action of colgate

e) Pick up and place action of block1

Fig. 9: Estimated axiomatic state from APF along with its point cloud view (left). Frames of robot performing the task of stacking is shown (right) from initial complex configuration to arbitrary *Tower of Colgate* goal configuration.

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