Learning Tabletop Object Manipulation by Imitation

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Abstract—We aim to enable robot to learn tabletop object manipulation by imitation. Given external observations of demonstrations on object manipulations, we believe that two underlying problems to address in learning by imitation is 1) segment a given demonstration into skills that can be individually learned and reused, and 2) formulate the correct RL (Reinforcement Learning) problem that only considers the relevant aspects of each skill so that the policy for each skill can be effectively learned. Previous works made certain progress in this direction, but none has taken private information into account. The public information is the information that is available in the external observations of demonstration, and the private information is the information that are only available to the agent that executes the actions, such as tactile sensations. Our contribution is that we provide a method for the robot to automatically segment the demonstration into multiple skills, and formulate the correct RL problem for each skill, and automatically decide whether the private information is an important aspect of each skill based on interaction with the world. Our motivating example is for a real robot to play the shape sorter game by imitating other’s behavior, and we will show the results in a simulated 2D environment that captures the important properties of the shape sorter game. The evaluation is based on whether the demonstration is reasonably segmented, and whether the correct RL problems are formulated. In the end, we will show that robot can imitate the demonstrated behavior based on learned policies.

I. INTRODUCTION

When a robot is presented with an unfamiliar object, the robot is not aware of what actions can cause what changes to the state of the object. Learning by imitation is an effective way for a robot to gain knowledge about possible useful actions on objects in its environment.

Given an observed behavior, usually formally defined as state variables describing the observed environment and action variables describing the observed actions, the robot should be able to learn a policy, which is a mapping between states and actions, such that it can select an action to execute based on its current state. RL methods are popular for policy learning, and the robot can improve its performance overtime through interaction with the world, thus we use RL methods in our work.

To learn a policy, we should first define a RL problem, usually formulated as an MDP (Markov Decision Process) with following components: the reward function, the action space, and the state space. The importance of formulating the correct RL problem, i.e., correctly defining each component is as explained below.

What is the importance of correctly defining the reward function? For a robot to learn to effectively manipulate an unfamiliar object by imitating other’s behavior, it is important for the robot to understand what to imitate, i.e., the goal of the behavior. For robotic experts, they can directly hand code the corresponding criteria to define the goal for the robot, but it is not realistic for most of the consumers of commercial robots to do so.

Thus it is important for the robot to automatically capture the goal of an observed behavior by defining the correct reward function. For example, if the goal of an observed behavior is to reach and grasp a cup, then the reward function can be defined as -1 everywhere except for a big positive reward when then cup is being grasped.

What is the importance of correctly defining the state and action space? Think of the way we act in our daily lives, when we manipulate some objects of interest, we don’t pay much attention to other objects in the environment. For example, if there are two blocks and a cup on a table, when we are stacking the two blocks, we don’t really care about where the cup is; on the other hand, when we try to put one of the block into the cup, we don’t care where the other block is. This reflects that even we are accessible to a bunch of information, we always abstract out the most important information relevant to our task by hand, and this is formally referred as abstraction in machine learning. RL problems that involve high-dimensional, continuous state and action space are difficult to solve, thus abstraction is a key to reduce the dimension of the problems. With the correct abstraction, the appropriate state and action space is defined for the RL problems.

In our work, we aim to find the abstraction that is able to 1) capture the important aspects of the behavior, and 2) chooses the correct reference frame (i.e., decides the target object) and relevant objects. As in our experiments, if the observed behavior is hand reaching for a block with a basket as a noise object in the environment, then the block is the target object, the robot should be able to decide to abstract out the distance and angle of the hand in the block frame as the state space, and further RL methods can be applied with that state space.

What if there are multiple RL problems involved? The observed behavior can underlie multiple policies, i.e., there are several skills involved in the behavior. For example, picking up a block, and then stacking it onto another one are two different skills. When the observed behavior contains multiple skills, the robot should be able to automatically segment the behavior into multiple pieces, each corresponds to a skill, and formulate different RL problems for each of them. The segmentation can be done based on how likely a temporal
A potentially useful manipulation behavior representation for artificial agents should satisfy several criteria. As pointed out in [2], the representation needs to be based on sensory signals and learnable by observation. From the point of view of learning by imitation, the representation should also satisfy that (1) it is not redundant in the sense that it should not encode information that exists only within certain observed behaviors, such as specific motion trajectories of human arm joints and objects; (2) it should be simple such that it can be easily interpreted as a roadmap that guide an agent to act. Previous works on human manipulation actions recognition have attempted to represent manipulation behavior in a probabilistic manner. Human poses, human-object context, and object-object context have been considered to solve the problem jointly as in [3]. Similarly in works by Kjellstrom et al. [4], pre-defined hand-object features and manipulation features are extracted, and the semantic manipulation action-object dependencies are learned based on CRFs. Their representation of manipulation behavior is powerful in that they can recognize manipulation actions as well as object categories. Although previous works are robust in manipulation action recognition when presented by various view points and even occlusions, those representations of the behavior cannot be directly translated into any step by step guidance, or a roadmap that an agent can follow for effective imitation. Works by Aksoy’s group [2] revealed an effective way to represent manipulation behavior. By observing different human demonstrations of the same manipulation behavior, they discovered that the manipulator, i.e. hand, and objects movement trajectory may vary, but there are certain moments that the spatial relations between the hand and objects are similar or identical across all the demonstrations, and these moments are referred as decisive moments. They introduced Semantic Event Chain (SEC) as a novel, generic representation of manipulation behavior, where they encoded the spatial relations between the manipulator and objects only at decisive moments.

B. Learning by Imitation

Some previous works learn movements by imitating joint trajectories [5][6][7]. They mounted sensors on human body, and recorded the joint angles during the demonstrations to teach humanoid robot drumming and walking patterns. While in our work, the robot needs to learn a manipulation task, directly imitating exact joints trajectories for manipulation tasks won’t generalize well. Two completely different sequences of joints trajectories can be performing the same manipulation task. For example, when we pick up an object, we can approach it from various angles and along various joint trajectories, but all these trajectories correspond the same manipulation task. Thus what really matters in the learning of a manipulation task is to capture and imitate the important aspects of the behavior rather than imitating the quantitative joints trajectories. For example, the important aspects of picking up an object are the hand needs to approach and get in contact with the object first, then grasp it to lift it up, no matter what the joints trajectories are. Another problem of imitating the joints trajectories is the corresponding issue. The corresponding issue is understood as the identification of a mapping from the demonstrator to the robot that allows the transfer of information. For example, in the case of robot learning to walk by observing human joint angles during demonstrations, before it can imitate the walking pattern, the robot needs to know the mapping between the human joint angles and its own joint angles.

There have been some works that directly learn the mapping from state to action. In robot domain, the state space is usually continuous, and the action space can be continuous or discrete.
Continuous action space can be composed by available sensor values, such as moving speed, joint angular speed, and torque. Discrete action space can be composed by discrete low level incremental actions, such as move forward by 0.1 meter for a mobile robot, or composed by discrete high level primitive actions, such as reach, grasp an object for a manipulator.

When the action space is discrete, the problem of learning the mapping is essentially a classification problem. For example, Chernova et al. [9][10] learns to navigate through corridors by observing the behavior generated by expert teleoperation. In their work, the states are continuous variables describing the distances of the closets walls, and the actions are discrete variables corresponding to pre-defined controllers that drives the robot forward, to the left, to the right, and u-turn. The mapping from state to action is learned based on GMM. Similar works have been focused on high-level primitive actions such as hand gestures, for learning box and ball sorting tasks [11][12]. When the action space is continuous, the problem of learning the mapping is then a regression problem. Grollman et al. [13] has applied locally weighted projection regression to soccer skill learning task on an AIBO robot.

Our work focus on automatically formulating RL problems for the skills observed in demonstration, and solving the RL problems result in good policies that can generate behaviors that imitate the observed demonstration. The most similar work is by Konidaris et al. [1]. There are also some works that focus on learning the correspondence, i.e., the mapping between the observed states/actions and the robot state/actions. In our work, we assume that the correspondence is known. For more details on works that solves the correspondence issue, please refer to this survey [8].

III. NOTATIONS

First of all, $S$ is the overall state space, and it divides into the overall public state space $S_{\text{public}}$ and the overall private state space $S_{\text{private}}$. In $S_{\text{public}}$, each dimension is a public state variable whose value can be externally observed, such as the $x$ coordinate of an object center, and a boolean state variable whose value can be externally observed, such as the open hand. $S_{\text{private}}$ is the overall state space, and it divides into the overall public state space $S_{\text{public}}$ and the overall private state space $S_{\text{private}}$. All the pose vectors in the observations are sampled frame, and $S_{\text{public}}$ is the overall state space, and it divides into the overall public state space $S_{\text{public}}$ and the overall private state space $S_{\text{private}}$. Each dimension is a public state variable whose value cannot be externally observed, such as tactile sensations on the fingers.

The robot observes a sequence of states sampled at the frame rate,
\[ O = \{s_0, s_1, \ldots, s_{\text{final}}\} \]
where $s_i \in S_{\text{public}}$. More specifically, $s_i$ is a vector composed of the pose vectors of objects in workspace, and the pose vector of hand,
\[ s_i = [P_i^{o_1}, P_i^{o_2}, \ldots, P_i^{h}]^T \]
where $P_i^{o_j}$ is the pose vector of the $j$th visible object at $i$th sampled frame, and $P_i^{h}$ is the pose vector of the hand at $i$th sampled frame. All the pose vectors in the observations are in the world frame, they can be transformed into any object frame or the hand frame given the object or hand pose.

Robot action space $A$ is composed by hand movements (translation and rotation in 3D), open and close gripper (with a default force), open and close gripper with commanded force. Given the observation, we define the action $a_i \in A$ taken at state $s_i$ to be
\[ a_i = [d(P_i^{h}, P_{i+1}^{h}), \text{open}(\alpha)]^T \]
where function $d$ returns the displacement between the hand poses $P_i^{h}$ and $P_{i+1}^{h}$ and $\text{open}(\alpha)$ defines the opening or closing grippers with force $\alpha$ (positive for opening, negative for closing, and zero for doing nothing). Note that the force $\alpha$ in action $\text{open}(\alpha)$ is not externally observable, thus $\alpha$ should be learned by robot explorations if that is considered an important aspect of the demonstrated behavior.

Demonstrations on tabletop object manipulations can involve multiple skills, for example, grasp and pick up a cup, the series of actions can be segmented into three individual skills: first, approach the cup; second, grasp the cup; third, lift the cup. Each skill is formally defined as an option $o$, as introduced in [14]. An option includes three components: 1) an option policy $\pi(o, s, a)$ which gives the probability of executing each action in each state in which the option is defined; 2) an initiation set indicator function $I_o(s)$ which gives 1 for states where the option can be executed and 0 elsewhere; 3) termination condition $\beta_o(s)$ which gives the probability of option execution terminating in states where it is defined.

When a demonstration is segmented into a sequence of skills, and each skill is represented as an option, the reward can be synthesized as negative at each step of action and positive when the option terminates. In this way, the goal of each skill is embedded in the termination condition, and can be captured by the synthesized rewards, as a simple instance of inverse reinforcement learning methods. These synthesized rewards are reasonable since many tabletop object manipulations involve skills with its own ending goal. If the real reward function is more complex than that, other inverse reinforcement learning methods [15] can be applied to infer the reward function from the demonstration.

The advantage of breaking the demonstration into a sequence of skills and learn the corresponding option is that: a) learned options can be reused in other tasks; b) to learn the option policy for each option, RL problem can be formulated with the state and action space composed by the most relevant state variables (can contain both public and private state variables) and action variables, instead of the overall state and action space.

We design a library of abstractions, where each abstraction $M$ is a pair of functions $(\sigma_M, \tau_M)$, where
\[ \sigma_M : S \mapsto S_M \]
is a state abstraction that maps the overall state space $S$ to a smaller state space $S_M$, and
\[ \tau_M : A \mapsto A_M \]
is an action abstraction that maps the full action space $A$ to a smaller action space $A_M$. In our work, the abstracted space $S_M$ and $A_M$ are subset of $S$ and $A$, with variables possibly described in a different reference frame rather than the world frame.
To formulate the correct RL problem for each segmented skill, the pair of state and action abstraction $M$ that involves the more important aspects of the skill should be selected.

IV. LINEAR VALUE FUNCTION APPROXIMATION

The value function $V$ maps a given state vector to expected return, and it can be approximated as a linear combination of a given set of basis functions $\Phi = \{\phi_1, \cdots, \phi_k\}$.

$$\hat{V}(s) = \sum_{i=1}^{k} w_i \phi_i(s)$$

where the basis function are Fourier basis, a generic basis that generally exhibits good performance [16]. The 2nd order Fourier basis for $d$ state variables in the set of basis function are defined as

$$\phi_i(s) = \cos(\pi c^i \cdot s)$$

where $c^i = [c_1, \cdots, c_d]$, $c_j \in [0, \cdots, z]$ with $1 \leq j \leq d$. The set of basis functions is obtained by systematically varying the coefficients $c_j$.

From the synthesized rewards we can obtain a Monte Carlo sample of expected return from each appeared state $s$,

$$R(s) = \sum_{i=1}^{n} \gamma^i r_i$$

where $\gamma$ is the discount factor, and $r_i$ is the synthesized reward. And $R(s)$ is the regression target for $\hat{V}(s)$ when we are trying to approximate the value function of the underlying policy in the demonstration, with a given set of Fourier basis functions.

Each abstraction $M$ in the abstraction library has an associated set of Fourier basis functions $\Phi_M$ defined over $S_M$. Therefore, abstraction selection amounts to selecting the set of basis functions that can best represent the value function inferred from the demonstration.

V. METHOD

We want to break the demonstration into multiple skills when it consist of underlying policies that use different abstractions, or it consists of policies that are too complex to be approximated using a single function approximator. Changepoint detection algorithm can be applied in this case to find the boundaries of each skill and select the best abstraction for each skill.

A. Changepoint Detection

First, I'll introduce the statistical changepoint detection in a general regression setting. Given observed data and a set of candidate models $Q$, we assume that the data are sequentially generated by an instance of a single model, occasionally switching to a different model or switching to a different instance of the same model at certain points in time, called changepoints. The goal is to infer the number and positions of the changepoints and select an appropriate model instance for each segment.

An efficient changepoint detection algorithm was introduced by Fearnhead and Liu [17] that obtains the MAP changepoints and models via an online Viterbi algorithm: given data tuples $(x_t, y_t)$ observed for times $t \in [1, 2, \cdots, T]$, and a set of candidate models $Q$ with prior $p(q)$ for each $q \in Q$. The marginal probability of a segment length $l$ is modeled with probability mass function $g(l)$ and cumulative mass function $G(l) = \sum_l = 1^l g(l)$. And a segment from time $j + 1$ to $t$ can be fit using model $q$ to obtain $P(j, t, q)$, the probability of the data segment conditioned on $q$. Functions $g(l)$ and $P(j, t, q)$ is either given as a prior knowledge or pre-learned based on some training data.

This results in a HMM where the hidden state at time $t$ is the model $q_t$ and the observed data is $y_t$ given $x_t$, as shown in Figure 1. The transition from model $q_i$ to $q_j$ occurs with probability

$$T(q_i, q_j) = g(j - i - 1)p(q_j)$$

The emission probability of an observed data segment starting at time $t + 1$ and continuing through $j$ using model $q$ is given by

$$P(y_{t+1} : y|q) = P(i, j, q)(1 - G(j - i - 1))$$

An online Viterbi algorithm can be used to compute $P_i(j, q)$, the probability of the changepoint previous to time $t$ occurring at time $j$ using model $q$ (i.e., from time $j + 1$ to $t$ the data is generated using model $q$) is

$$P_i(j, q) = (1 - G(t - j - 1))P(i, j, q)p(q)P_j^{MAP}$$

where $P_j^{MAP}$ is the probability of the MAP changepoint at time $j$,

$$P_j^{MAP} = \max_{i,q} P_i(j, q)g(j - i) / (1 - G(j - i - 1))$$

Thus at each time $t$, the algorithm computes $P_t(j, q)$ for each model $q$ and changepoint time $j < t$ (using $P_j^{MAP}$) and then computes and stores $P_t^{MAP}$. As $P_t^{MAP}$ being recursively calculated, the MAP changepoint positions and models are stored. When $P_t^{MAP}$ is calculated for the complete observed data sequence, the MAP changepoint positions and models for generating the observed data are identified as a result.
B. Demonstration Segmentation and Abstraction Selection

Our framework for simultaneous demonstration segmentation and abstraction selection is as shown in Figure 2. We apply the changepoint detection algorithm to segment the demonstration at time points where the abstraction changes and select the appropriate abstraction for each segment such that, 1) the observed behavior can be effectively captured by the basis functions associated with the selected abstraction; 2) the observed trajectory in the state space is simple. By default, only public state and action variables are considered, if the RL problem formulated with the abstracted public state and action space cannot reproduce the observed behavior, we will re-formulate the RL problem by adding in private state and action variables.

The set of candidate models $Q$ is composed by the sets of basis functions $\Phi_M$ associated with each abstraction $M$, and $R(s_t)$ at time $t$ is the target variable $y_t$. For the changepoint detection algorithm to work well, an appropriate model of expected segment length and an appropriate model for fitting the data are required. As introduced by Konidaris et al. [11], it is suggested to assume a geometric distribution for skill lengths with parameter $p$, so that

$$g(l) = (1-p)^{l-1}p$$
$$G(l) = 1 - (1-p)^l$$

and this provides a natural way to set $p$ via $k = 1/p$, the expected skill length.

A linear regression model with Gaussian noise is assumed to be the model of observed data, and the Gaussian noise prior has mean zero and an inverse gamma variance prior with parameters $\nu/2$ and $\alpha/2$. The prior for each weight is a zero-mean Gaussian with variance $\sigma^2 \delta$. The probability of the data segment from time $j+1$ to $t$ conditioned on abstraction $q$ is

$$P(j, t, q) = P_V(j, t, q)P_{traj}(j, t, q)$$

where $P_V(j, t, q)$ measures how well the basis functions associated with model $q$ approximate the value function $V$, and $P_{traj}(j, t, q)$ measures how simple the observed trajectory is in the abstracted state space,

$$P_V(j, t, q) = \frac{\pi^2}{\delta m/2} |(A_q + D)^{-1}|^{\frac{1}{2}} \frac{u^2}{(y_q + u)^{\frac{n+\nu}{2}}} \frac{\Gamma(\frac{n+\nu}{2})}{\Gamma(\frac{\nu}{2})}$$

$$P_{traj}(j, t, q) = \prod_{i=1}^{N} \frac{\pi^2}{\delta m/2} |(A + D)^{-1}|^{\frac{1}{2}} \frac{u^2}{(y_{o_k} + u)^{\frac{n+\nu}{2}}} \frac{\Gamma(\frac{n+\nu}{2})}{\Gamma(\frac{\nu}{2})}$$

where $n = t - j - 1$, $q$ has $m$ basis functions, $\Gamma$ is the Gamma function, $D$ is an $m \times m$ matrix with $\delta^{-1}$ on the diagonal and zeros elsewhere, $N$ is the number of relevant object indicated by the selected state abstraction. And

$$A_q = \sum_{i=k+1}^{t} \Phi_q(s_i) \Phi_q(s_i)^T$$
$$y_q = \sum_{i=j}^{t} R^T - b_q^T (A_q + D)^{-1} b_q$$
$$A = \sum_{i=k+1}^{t} \left[ \frac{1}{t-j} \frac{1}{(t-j)^2} \right] [1, \frac{1}{t-j}, \frac{1}{(t-j)^2}]$$
$$y_{o_k} = \sum_{i=j}^{t} d_{o_k}(s_i)^2 - b_{o_k}^T (A_{traj} + D)^{-1} b_{o_k}$$

where $\Phi_q(s_i)$ is a vector of $m$ basis functions associated with model $q$ evaluated at state $s_i$, $R_i = \sum_{j=i}^{t} \gamma^{j-i} r_j$ is the accumulated reward obtained from state $s_i$, and $b_q = \sum_{i=j}^{t} R_i \Phi_q(s_i)$, $b_{o_k} = \sum_{i=j}^{t} d_{o_k}(s_i)[1, \frac{1}{t-j}, \frac{1}{(t-j)^2}]$, $d_{o_k}(s_i)$ is the distance between the end effector of the agent and selected relevant object $o_k$.

Using the probability functions defined above, the changepoint detection algorithm can segment the demonstration into multiple skills with selected abstraction. Once the RL problem is formulated for each skill, an initial policy can be learned based on the demonstration and the robot can improve upon the initial policy using appropriate RL methods. In our experiments, we use Sarsa($\lambda$) learning as our RL method, and if the policy learned after maximum number
of trials cannot successfully reproduce the observed behavior, our framework handles that by automatically reformulate RL problem by adding in private state and action variables, e.g. tactile sensation state variable and gripping opening/closing action in our experiment.

VI. EXPERIMENT

A. Shape Sorter Game

Our motivating example is the shape sorter game, as shown in Figure 3(a) the goal is to pick up a block and align it with the corresponding shape hole and push it into the box. Now let’s assume there are only the box and the green block within the visible field, as shown in Figure 3(b) and the demonstrator demonstrates the inserting the green block into the box.

The overall public state space will contain the pose of the block $P_{\text{block}}$, the box $P_{\text{box}}$ and the hand $P_{\text{hand}}$ in a world frame. The overall private state space will contain the private tactile sensation on the left and the right fingers $\lambda', \lambda''$. The action space is as introduced earlier. There are three coordinate frames available in this case, i.e., the world frame, the block frame, and the box frame.

B. The Abstraction Library

We aim to design an abstraction library that is sufficient for the tabletop object manipulations such as assembly tasks, such that the proper abstraction exists for any tabletop object manipulation skill that the robot may decide to learn.

We define the mapping functions $\langle \sigma_M, \tau_M \rangle$ of an abstraction $M$ by two sets of parameters $\langle \mathbf{P}_\sigma, \mathbf{P}_\tau \rangle$:

\[
\mathbf{P}_\sigma = [I_L, I_O, I_A, I_{o_1}, I_{o_2}, \ldots, I_J, C]
\]

\[
\mathbf{P}_\tau = [I_T, I_R, I_F]
\]

where each parameter is a binary digit. In $\mathbf{P}_\tau$, if $I_T=1$, then hand translation action is included in the abstracted action space $A_M$; if $I_T=0$, then it is not included in $A_M$. Similarly, $I_R$ indicates whether hand rotation action is included in $A_M$, and $I_A$ indicates whether opening/closing with commanded force is included in $A_M$. In $\mathbf{P}_\sigma$, $I_L, I_O, I_A$ indicate whether location variables, orientation variables, and tactile sensations are included in $S_M$, and $I_{o_1}, I_{o_2}, \ldots, I_h$ indicate whether information of objects $o_1, o_2, \ldots$ and hand $h$ are included in $S_M$, and $C$ indicates the reference frame in which the information should be represented. For example, $\mathbf{P}_\sigma = [I_L = 1, I_O = 0, I_A = 0, I_{o_1} = 0, I_{o_2} = 1, C = C_{\text{box}}]$ indicates that $\sigma_M$ maps $S$ to $S_M$, where the state variables are locations of the block and hand expressed in the box frame.

Note that when only hand translation action is included in $A$, i.e., $\mathbf{P}_\tau = [1, 0, 0]$, the state variables that the action can affect are the location variables, thus it is reasonable to constrain $S_M$ to include only location variables in this case, i.e., $I_L, I_O, I_A = [1, 0, 0]$. And the same principle applies to $\mathbf{P}_\tau = [0, 1, 0]$, $\mathbf{P}_\tau = [0, 0, 1]$, $\mathbf{P}_\tau = [1, 1, 0]$ and so on. As a result,

\[
[I_L, I_O, I_A] = [I_T, I_R, I_F]
\]

is a rule of thumb for designing the abstraction library.

By enumerating all possible pairs of parameters $\langle \mathbf{P}_\sigma, \mathbf{P}_\tau \rangle$ under the constraint $[1]$ the abstraction library is built with the resulting mapping functions $\langle \sigma_M, \tau_M \rangle$. The size of the abstraction library is $2^{r_\lambda^l-1} K$, where $K$ is the number of available coordinate frames.

C. Simplified 2D Manipulation Domain

Our toy example that captures the important properties in our motivating example is a 2D manipulation domain, where a robot, block, and a basket is involved. The observed behavior is the hand (or robot) reaches the block first and then translates it into the basket, as shown in Figure 4.

D. Evaluation

Given the external observations of a demonstration as shown in Figure 5(a) and assuming reasonable perception errors, the evaluation is mostly concerned of 1) whether the demonstration is reasonably segmented into multiple skills, and 2) whether the correct RL problem is formulated for each segmented skill, including whether the private information is considered in the RL formulation when it is actually important. Videos of the robot learning to reproduce the observed behavior are available at https://www.dropbox.com/seltxl0ssolevwn0/QUAL2_ZHEN_slides.pptx?dl=0.

Given two different sample trajectories, the segmentation results were successful. And the selected abstraction is also correct. In both experiments, for the 1st segment, the abstraction is selected as robot and block distance and angle w.r.t the block frame; for the 2nd segment, the abstraction is selected as robot and block distance and angle w.r.t the basket frame.

And the RL problem initially formulated for the 2nd segment only involves public state and action variables, which is incorrect, since to carry the block to the destination basket, the robot needs to incorporate holding action. Thus the robot failed to reproduce the observed behavior in the 2nd segment.
and reformulate the RL problems if needed. When private information is not available in the observed behavior, the robot frame and relevant objects are chosen. And when private observed behavior is captured, and 2) the correct reference needed, and select the appropriate abstraction such that 1) the behavior, we can segment the behavior into multiple skills if converged, the robot learned to exert enough holding force onto the block while carrying it to the basket.

which result in reformulation of the RL problem by adding tactile state variable into originally selected $S_M$, and adding holding action into originally selected $A_M$. Then $Sarsa(\lambda)$ is applied again in the reformulated RL problem, when the policy converged, the robot learned to exert enough holding force onto the block while carrying it to the basket.

### VII. Conclusion

We show that based on our framework, given observed behavior, we can segment the behavior into multiple skills if needed, and select the appropriate abstraction such that 1) the observed behavior is captured, and 2) the correct reference frame and relevant objects are chosen. And when private information is not available in the observed behavior, the robot is able to decide whether the private information is important, and reformulate the RL problems if needed.

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