Composable Causality in Semantic Robot Programming

Emily Sheetz, Xiaotong Chen, Zhen Zeng, Kaizhi Zheng, Qiuyu Shi, Odest Chadwicke Jenkins
Laboratory for Progress
University of Michigan, Ann Arbor, MI, USA

Introduction

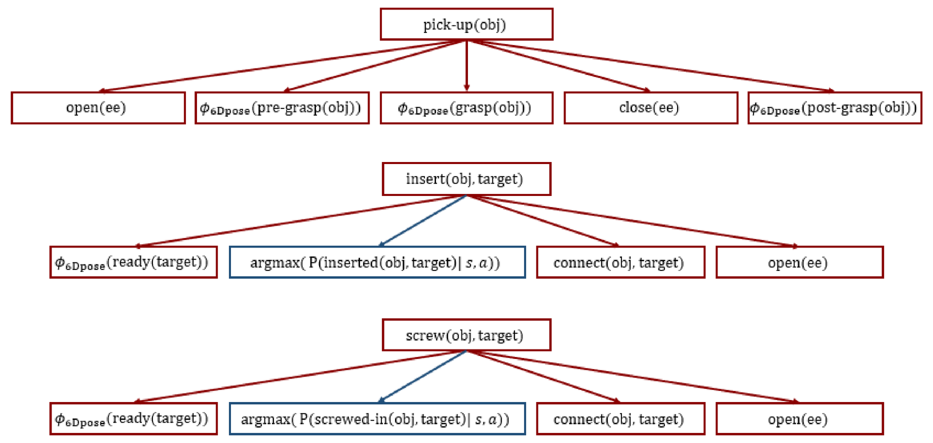
Assembly tasks present unique challenges in reasoning over objects, predicting the composed effects of actions, and executing complex behaviors in long-horizon tasks. *Object-centric controllers* [1] allow robots to achieve low-level motion primitives and can be *composed*—run concurrently with priorities between the behaviors—to perform *multi-objective actions* [2], such as those required in assembly tasks. Priorities between behaviors are generally hard-coded based on user experience, but we want robots to autonomously compose controller behaviors without relying on pre-defined priorities [3]. To autonomously compose controllers in long-horizon assembly tasks, the robot is given hierarchical causal information [4]. Our proposed *causal control basis* extends the intuitive declarative programming of the Semantic Robot Programming (SRP) paradigm [5] and allows the robot to autonomously predict the effects of multi-objective actions and achieve challenging goal-directed manipulation in furniture assembly tasks.

Causal Control Basis

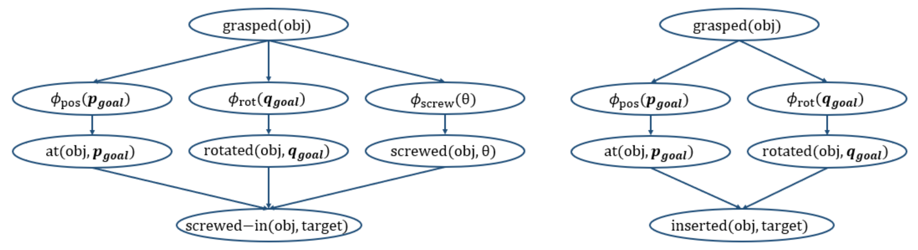
The *causal control basis* $\mathbf{\Phi} = (\Phi, G_T, G_C)$ is given to the robot and is comprised of:

- Controllers in the control basis Φ (pose, position, rotation, and screw controllers)
- Temporal graphs G_T showing the sequence of controllers that correspond to high-level symbolic actions
- Causal graphs G_C showing what controllers are involved in a multi-objective action

The robot will use the *causal control basis* to predict the composed effects of compositions of controllers and execute the composition most likely to achieve its composed effects.



Temporal graphs for high-level actions.



Causal graphs for multi-objective *insert* and *screw* actions.

Composed Causality Predictions

The *causal control basis* predicts the composed effects of a controller composition by estimating the transition probability of the composition based on a simulated execution of the action a and averaging across many executions:

$$a = \phi_k \lhd \phi_j \lhd \phi_i$$

$$\hat{P}(s' \mid s, a) = \begin{cases} 1 & \text{objectives met} \\ 0 & \text{bad progress} \\ \frac{\phi_a(s) - \phi_a(s_T)}{\phi_a(s)} & \text{otherwise} \end{cases}$$

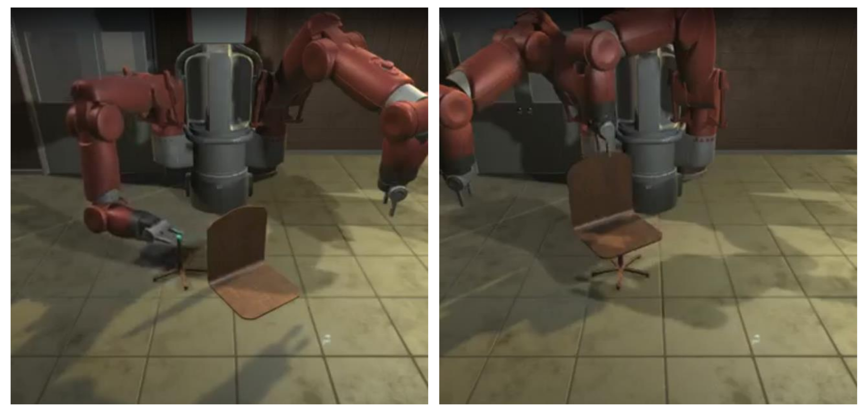
Composition a	Predicted Transition Probability $\hat{P}(s' \mid s, a)$
$\phi_{pos} \lhd \phi_{rot}$	**0.723**
$\phi_{rot} \lhd \phi_{pos}$	0.711

Composition a	Predicted Transition Probability $\hat{P}(s' \mid s, a)$
$\phi_{rot} \lhd \phi_{screw} \lhd \phi_{pos}$	**0.937**
$\phi_{pos} \lhd \phi_{screw} \lhd \phi_{rot}$	0.936
$\phi_{screw} \lhd \phi_{pos} \lhd \phi_{rot}$	0.929
$\phi_{pos} \lhd \phi_{rot} \lhd \phi_{screw}$	0.925
$\phi_{screw} \lhd \phi_{rot} \lhd \phi_{pos}$	0.923
$\phi_{rot} \lhd \phi_{pos} \lhd \phi_{screw}$	0.904

Transition probability predictions for *insert* (top) and *screw* (bottom) actions, based on 500 walkouts for each composition.

Multi-Objective Furniture Assembly Tasks

We test our *causal control basis* in the IKEA Furniture Assembly Environment [6] simulator on the Baxter robot. The *causal control basis* uses its predictions to convert the output from an off-the-shelf task planner [7] into a sequence of (composed) controllers. The robot uses multi-objective *insert* and *screw* actions to successfully assemble a chair and a table in several random trials. Our work demonstrates that the proposed *causal control basis* accurately predicts the composed causality of multi-objective actions and provides the declarative knowledge necessary for robots to autonomously compose controllers.



Chair assembly with multi-objective *insert* action. (action success rate 0.714; task success rate 1)

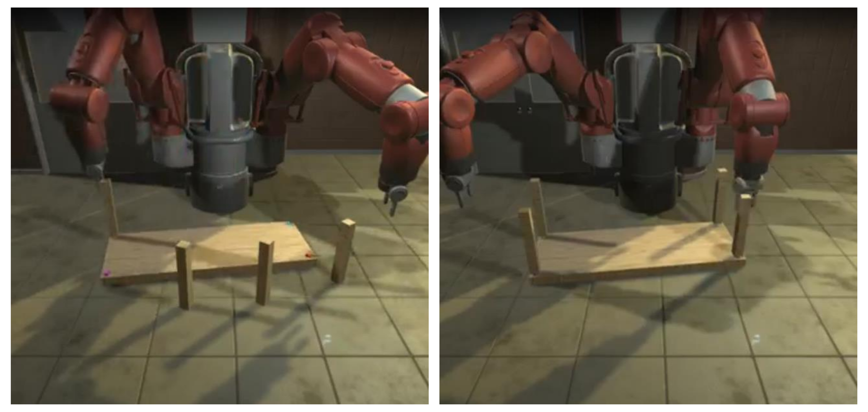


Table assembly with multi-objective *screw* action. (action success rate 0.952; task success rate 1)

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This work was supported in part by NASA Space Technology Graduate Research Opportunity (NSTGRO) grant number 80NSSC20K1200.