Learning to Switch between Sensorimotor Primitives using Multimodal Haptic Signals

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***Abstract*—Most manipulation tasks can be decomposed into sequences of sensorimotor primitives. These primitives often end with characteristic sensory events, e.g., making or breaking contact, which indicate when the sensorimotor goal has been reached. In this manner, the robot can monitor the tactile signals to determine when to switch between primitives. In this work, we present a framework for automatically segmenting contact-based manipulation tasks into sequences of sensorimotor primitives based on multimodal haptic signals. These signals include both the robot's end-effector position as well as the low- and high-frequency components of its tactile sensors. The resulting segmentation is used to learn to detect when the robot has reached a sensorimotor goal and it should therefore switch to the next primitive. The proposed framework was evaluated on guided peg-in-hole tasks. The experiments show that the framework can extract the subtasks of the manipulations and the sensorimotor goals can be accurately detected.**

I. Overview

Manipulation tasks typically involve executing a series of discrete sensorimotor primitives. For example, humans pick and place objects by grasping, lifting, transporting, placing, and releasing the objects. These primitives are usually bound by mechanical events that represent sensorimotor subgoals of the task [4], e.g., making/breaking contact between either the hand and an object or a grasped object and another object.

These changes in the contact state result in discrete and distinct sensory events that are characterized by specific neural signatures in human tactile afferents [4]. For example, when fingers make contact with an object during grasping, signals from the slow- and fast-adapting type one afferents (SA-I, FA-I) provide information about the outcome of the grasp. Similarly, the FA-II afferents detect the contact vibrations during tool use when contact between the grasped object and another object is made/broken or when slip occurs. Tactile events indicate suitable segmentation points of sensorimotor primitives because they are implicitly detecting when the constraints of the task change [2, 3, 5].

In this work, we present a framework (Fig. 1) for segmenting manipulation tasks into sensorimotor primitives and subsequently learning to switch between these primitives based on tactile events. The primitives are segmented such that they each terminate with a sensory event, as shown in Fig. 1. These sensory events have a short duration, which we assume to be 160ms long. Bayesian on-line changepoint detection (BOCPD) has been used to segment demonstrated manipulation tasks by detecting changes in the relative pose of two objects or parts of articulated objects [7]. Given the importance of high frequency tactile signals in manipulation tasks [8], our approach incorporates multimodal haptic signals into the BOCPD [1]. Each changepoint indicates a sensorimotor subgoal of the task. The haptic time series signals include the Cartesian position of the robot's hand and the low- and high-frequency signals of the tactile sensors.

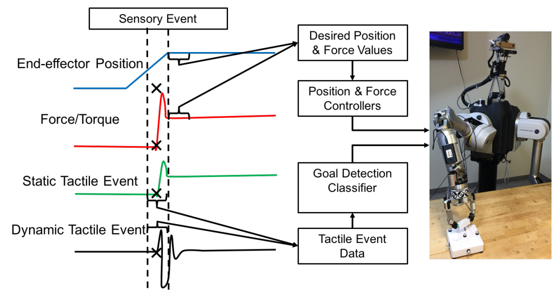

Fig. 1: Illustration of our framework of segmentation of sensorimotor primitives from demonstrated trajectories.

The sensory signals observed during the sensory event (changepoint) are used to train a goal detector by learning a classifier for detecting the sensory event when the primitive is executed (Fig. 1). In this manner, the robot can monitor whether the subgoal has been reached and switch to the next sensorimotor primitive accordingly. Rather than manually designing features for representing the haptic signals, the robot uses Spatio-Temporal Hierarchical Matching Pursuit (ST-HMP) [6] to learn features. The detection of the sensory events is then achieved using linear support vector machines.

The position and force signals 100ms after the sensory event are used to compute the desired state for the controller (Fig. 1). The feedback gains for the controllers are predefined. The desired force is incrementally increased by 1N, if the primitive failed to reach the desired sensory event. The desired position is defined relative to the starting position of the skill. Thus, if a skill terminates early, the following primitives' desired positions are offset accordingly.

II. Evaluation and Discussion

The proposed framework was evaluated using guided peg-in-hole tasks. The experiments evaluated the segmentation using different sets of sensor modalities, and the accuracy of the classifiers for switching between sensorimotor primitives.

A. Sensorimotor Primitives Segmentation for Peg-in-hole tasks

We evaluated our method on our robot platform. For the guided peg-in-hole tasks, we use a 3D printed peg-in-hole set consisting of holes with 1mm clearance and various geometric features, including a curved groove leading into a hole, a straight groove leading into a hole, and a squared groove with a hole at one of its corners, as shown in the inset of the left picture of Fig. 2. These features are designed to create constraints that guide the robot while performing the peg-in-hole tasks. Interacting with these geometric features results in tactile events. The robot should therefore learn sequences of sensorimotor primitives that reach the individual geometric features, and switch between the primitives accordingly to perform the task.

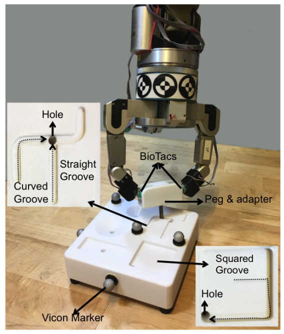

Fig. 2: Experimental setup for peg-in-hole.

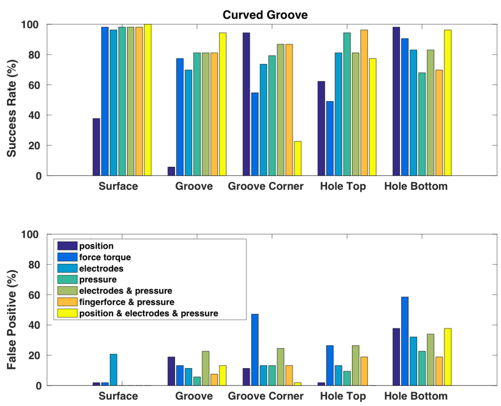

Fig. 3: Segmentation success rate and false positive rate.

The joint BOCPD on the multimodal signals performed better than the independent BOCPD on the uni-modal signals. Fig. 3 show the segmentation success rates and false positive rates for sensorimotor events in a guided peg-in-hole task with the curved groove. The multimodal tactile signals, including the electrodes and pressure sensors, usually achieved the highest success rates and the lowest false positive rates. This result is due to the changepoints of joint BOCPD using the effects of both the low- and high-frequency sensory information. Thus, the joint model can extract more information from the data as simultaneous changes in multiple time series is a stronger indication of a sensorimotor changepoint.

B. Sensorimotor Primitives Goal Detection

We evaluated the sensorimotor primitive goal detection method on three peg-in-hole tasks. We use the changepoints detected using the kinethetic and tactile data. For each changepoint detected by the segmentation method, except the first changepoint, we train a binary classifier to classify a total of 16 sensory data samples directly before and after the changepoint against 16 samples randomly selected between the last changepoint and the current changepoint. The goal is to have the robot autonomously detect whether it has reached the current sensorimotor primitive's goal, and should therefore terminate the current primitive and switch to a new one.

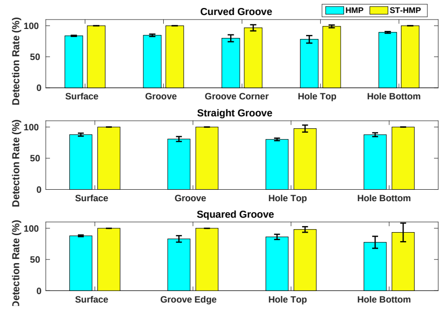

Fig. 4: Peg-in-hole sensorimotor primitive detection results.

To evaluate the HMP and ST-HMP approach for the classification of sensorimotor primitives, we perform a 5-fold cross-validation on the data set by using 20% of the data as the test set and the remaining samples to train the classifier. Fig. 4 shows the classification accuracies and the standard deviations for the different sensorimotor primitives. Each of the primitives has 28 training trials and 7 test trials. By using all tactile sensor modalities, the average accuracies among the different sensorimotor primitives range from 77.5% to 100%.

Overall, the ST-HMP achieves higher accuracy and lower standard deviation than the HMP. The difference between ST-HMP and HMP is that ST-HMP combines the tactile information from multiple time steps t to create the features. In contrast, HMP creates features for each time step and then concatenates them. The ST-HMP also incorporates pooling over the time steps, which results in temporal invariances. The results thus show the importance of combining information from multiple time scales when detecting sensory events.

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