Slip Classification Using Tangential and Torsional Skin Distortions on a Biomimetic Tactile Sensor

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I. Introduction

There are two main categories of object slip: linear and rotational. During linear slip, the object maintains its orientation with respect to the local end-effector frame but gradually slides out of the robot fingers. During rotational slip, the center of mass of the object tends to rotate about an axis normal to the grasp surface, although the point of contact with the robot's fingers might stay the same. It is important to discriminate between these two kinds of slip to react and control finger forces accordingly. Previous study has shown rotational slip requires much stronger finger force response than linear slip in order to robustly keep the object grasped within the hand [1].

We have developed a haptically-enabled robot with the Barrett arm/hand system whose three fingers are equipped with novel biomimetic tactile sensors (BioTacs) (Fig. 1). Each BioTac consists of a rigid core housing an array of 19 impedance-sensing electrodes surrounded by an elastic skin.

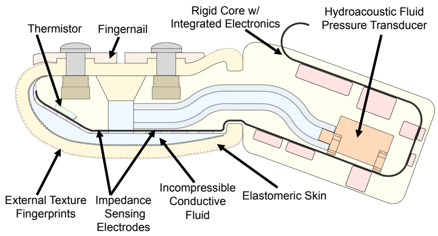

Fig. 1 Cross-sectional schematic of the BioTac sensor

When an object is grasped by a pinch grip (Fig. 2), the skin distortions, measured by the electrodes on the BioTacs, should be very different prior to linear slips or rotational slips. Thus, the likelihood of a given slip will be a particular type given the prior skin distortions between the skin and the object. This paper demonstrates a slip classifier that is able to classify the types of slip based on different skin distortions with over 80% accuracy before an IMU detects that the object is moving.

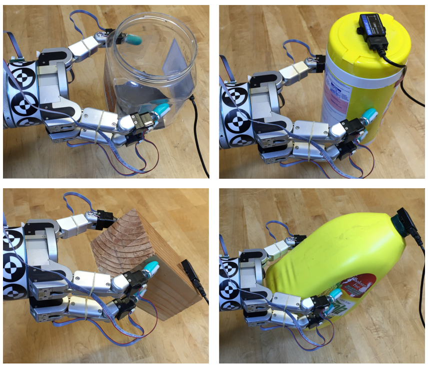

Fig. 2: Different objects used for the experiments.

II. Approach

To be able to classify linear and rotational slip, we train a neural network to learn the mapping from the time-varying BioTac electrode values of the tangential vs. torsional distortions of the skin to the corresponding slip class. To construct the features, we take a certain time interval of electrode values and combine all values inside the window into one long feature vector, i.e. 100 consecutive timestamps of 19-dimensional electrode values result in a 1900-dimensional input vector. The architecture of the NN consists of input, output and one hidden layer with 50 neurons. The hidden layer has a sigmoid transfer function. The softmax activation function is used in the output neurons. It produces the probabilities of the signal sequence belonging to one of the slip classes.

In order to avoid overfitting of the training data we employ the early stopping technique during training. The network is trained with the Scaled Conjugate Gradient back-propagation algorithm.

III. Evaluation and Discussion

To evaluate the NN approach for the classification of two kinds of slip events, four objects were chosen: a wooden block, oil bottle, wipes box and a jar with added weights (see Fig. 2). For training, the robot grasped an object either approximately at the center of mass of the object or at the edge of the object. These two grasping methods caused either linear (if grasped at the center of mass) or rotational slip of the object while it was being picked up. In order to detect slip, an IMU was attached to the object. For each object, over 80 grasps were performed (40 for the linear slip and 40 for the rotational slip). The data set was randomly shuffled and divided into the 80% training and 20% test sets. Similar to the force estimation, 20% of the training set was used for the validation during the NN training.

Results of the experiments are depicted in Fig. 3. For the input of the NN, points from 100 consecutive timestamps were selected, resulting in a 1900-dimensional input vector. Each point in Fig. 3 corresponds to the last timestamp that was taken into account as the NN input, i.e. the point when we classify slip given 100 previous values. The moment when slip was detected by the IMU is depicted by a vertical line. As more data are gathered during an actual slip, classification accuracy improves as expected. However, it is worth noting that using the NN approach, the robot is able to achieve approximately 80% classification rate, before the IMU is even able to notice that the slip event started. Our algorithm accurately detects the slip class even before significant object motion is detected (using an IMU), allowing more time for the robot to respond appropriately.

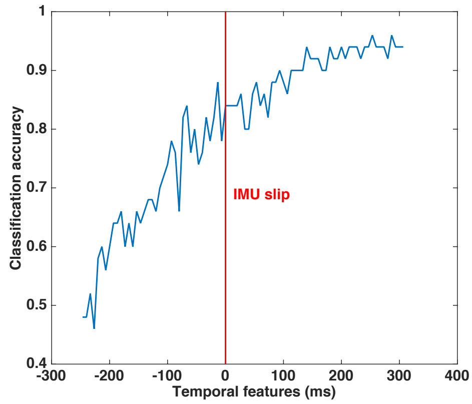

Fig. 3: Linear/rotational slip classification accuracy dependent on the time of prediction. Red line shows the point when slip is detected based on the IMU readings.

IV. Conclusion and Future Work

Slip classification into linear or rotational slip was observed to be important for robust object handling due to different requirements for finger force response. We achieved 80% classification success rate using a neural network approach before the slip event was detected by an IMU accelerometer. This indicates that the robot should be able to change finger forces at a very early stage of the slip and therefore, prevent the moving of the object inside the hand. In future work, this classifier along with tri-axial contact forces and incipient slip extracted from BioTac will be employed and evaluated in a grip force controller.

[1] Kinoshita, H., Bäckström, L., Flanagan, J. R., & Johansson, R. S. (1997). Tangential torque effects on the control of grip forces when holding objects with a precision grip. *Journal of Neurophysiology*, 78(3), 1619-1630.

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