Slip Detection and Classification for Grip Control using Multiple Sensory Modalities on a Biomimetic Tactile Sensor

Zhe Su Karol Hausman Yevgen Chebotar Artem Molchanov
Gerald E. Loeb Gaurav S. Sukhatme Stefan Schaal

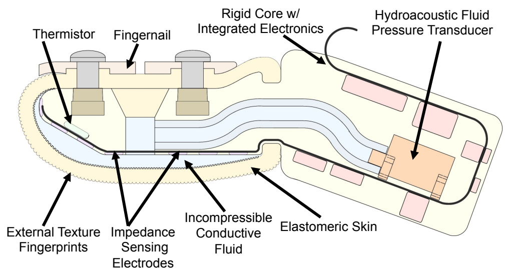

Fig. 1: Cross-sectional schematic of the BioTac sensor.

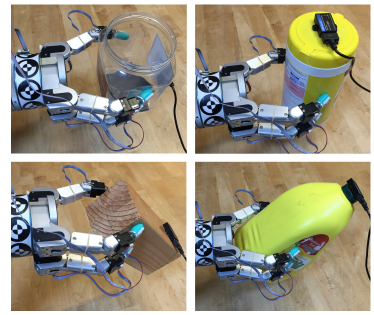

Fig. 2: Different objects used for the experiments.

I. Introduction

Achieving human-level performance in dexterous grasping tasks will likely require richer tactile sensing than is currently available [1]. Recently, biomimetic tactile sensors, designed to provide more humanlike capabilities, have been developed. These new sensors provide an opportunity to significantly improve the robustness of robotic manipulation. In order to take full advantage of the information available from such sensors, new estimation techniques have to be developed. Since these sensors provide different sensory modalities, one should also focus on how they can be combined in various manipulation tasks. This paper presents two estimation techniques that use different sensory modalities of biomimetic tactile sensors to detect and classify slip events during grasping. In particular, we present a slip detector, which is able to detect slips more than $30ms$ before it was detected by an IMU accelerometer. In addition, we demonstrate a slip classifier that is able to classify the type of slip based on different skin distortions with over 80% accuracy before an IMU detects that the object is moving.

II. Approach

A. Biomimetic Tactile Sensor - BioTac

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. The BioTac consists of three complementary sensory modalities: force, pressure and temperature. When the skin is in contact with an object, the liquid is displaced, resulting in distributed impedance changes in the electrode array on the surface of the rigid core. The impedance of each electrode tends to be dominated by the thickness of the liquid between the electrode and the immediately overlying skin. Slip-related micro-vibrations in the skin propagate through the fluid and are detected as AC signals by the hydro-acoustic pressure sensor. Temperature and heat flow are transduced by a thermistor near the surface of the rigid core.

Zhe Su and Gerald E. Loeb are with the Department of Biomedical Engineering; Karol Hausman, Yevgen Chebotar, Artem Molchanov, Stefan Schaal and Gaurav S. Sukhatme are with the Department of Computer Science, University of Southern California, Los Angeles. zhesu@usc.edu

B. Slip Detection

In order to detect a slip event, two different estimation techniques are used: a force-derivative method and a pressure-based method. In the force-derivative method, the tangential force sensed by the BioTac increases as the robot lifts an object while the normal force decreases. The ratio between normal and tangential forces thus decreases, indicating a transition to kinetic friction and hence slip. The negative derivative of the normal force is used to detect slip in this manner.

Slip is also detected using the pressure sensor. Because the BioTac skin contains a pattern of human-like fingerprints, it is possible to detect slip-related micro-vibrations on the BioTac skin when rubbing against textured surfaces. A band-pass filter (60-700Hz) is first employed to filter the pressure signal. Second, the absolute value of the signal is calculated because we are interested in the absolute vibration. Due to differences between pressure sensor sampling frequency ($2.2kHz$) and the robot's onboard controller ($300Hz$), the slip detection algorithm considers a $10ms$ time window (3 cycles of the onboard controller). This guarantees 22 samples of pressure readings in the time window. Slip is detected if 11 out of 22 pressure sensor values exceed the threshold. The slip threshold is found empirically to be twice as large as the baseline vibration caused by the motors of the robot.

C. Slip Classification

We classify slip into two categories: 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's 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 robots fingers might stay the same. The importance of these classes has been shown by a previous study [2], where the authors demonstrated that rotational slip requires much stronger finger force response than linear slip in order to robustly keep the object grasped within the hand.

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 to the 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, e.g. 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.

III. Evaluation and Discussion

A. Slip Detection

We tested our slip detection algorithms on two objects with distinctive textures: a plastic jar with a smooth surface and a wooden block with a rough texture (see Fig. 2). In both cases, we attached an IMU to the objects to detect the moment when the object starts moving. In order to induce slips, the robot lifts an object with insufficient force while the experimenter supports it; the experimenter then releases the object, causing it to slip. The collected data set consists of 20 slip events per object.

An example run of the slip detection experiment is depicted in Fig. 3. By using the force-derivative and the pressure-based methods, we were able to detect slip before it was noticed by the IMU. It is also worth noting that the pressure-based method can detect slip sooner than the force-derivative method. This may be caused by the fact that in the very initial stage of slip (incipient slip) the microscopical slip effects are not yet visible at the electrodes. Nonetheless, the slight movement of the fingerprints is picked up by the high-frequency pressure signal.

Statistical analysis of the experiments shows that the robot is able to detect slip using the force-derivative method $5.7ms \pm 4.5ms$ for the plastic jar and $7.8ms \pm 3.6ms$ for the wooden block before the movement is detected by the IMU. The pressure-based method detects slip even sooner: $32.8ms \pm 4.2ms$ for the plastic jar and $35.7ms \pm 6.0ms$ for the wooden block before the motion is detected by the IMU.

B. Slip Classification

We used four objects to evaluate slip classification: a wooden block, an oil bottle, a bottle of cleaning wipes 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 divided into the 80% training and 20% test sets.

Results of the experiments are depicted in Fig. 4. For the input of the NN, points from 100 consecutive timestamps were selected, resulting in a 1900-dimensional input vector. Each point in Fig. 4 corresponds to the point when we

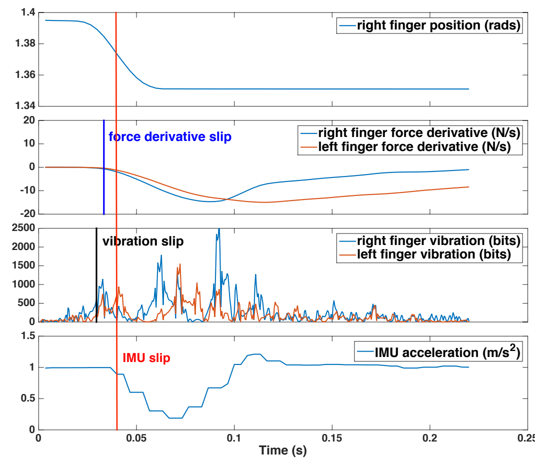

Fig. 3: An example run of the slip detection experiment.

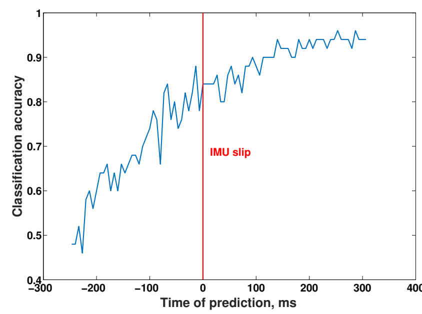

Fig. 4: Linear / rotational slip classification accuracy.

classify slip given 100 previous values. The moment when slip was detected by the IMU is depicted by a vertical line. As we approach the slip, the 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. During a manipulation task this would allow more time for the robot to respond appropriately.

IV. Conclusions and Future Work

This work demonstrated slip detection and classification using multiple sensory modalities on a biomimetic tactile sensor. Our method was able to detect slips more than $30ms$ before it was detected by an IMU accelerometer and achieve 80% slip classification success rate before the IMU detection. This indicates that the robot should be able to adapt finger forces at a very early stage of the slip and prevent the object from moving. In future work, we plan to fuse the estimation techniques presented in this paper to be able to take full advantage of the sensor and also employ other sensory modalities of the BioTac sensor.

References

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