Grasp Slip Prevention and Object Classification with an Underactuated Robotic Hand

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***Abstract*—Prosthetic devices are vital to the mobility and independence of people who have lost a limb. However, most prosthetic hands lack the ability to adjust their grip to combat object slippage when the user is unaware of such an event. This project aims to detect object slippage in a grasp and dynamically adjust the grip force to prevent the object from falling while minimizing object deformation. It also attempts to classify the rigidity of various objects. In order to accomplish this, a Reflex Takktile hand mounted on a Baxter robot was used.**

I. Introduction

Nearly 2 million Americans have missing limbs [1]. Despite advances in technology, there are a limited number of commercially available prosthesis that adjust gripping force after external forces are applied to the object being grasped [2]. In addition, there is a lack of proprioceptive feedback to amputees [3]. One solution to this problem could be to use object classification as a type of feedback for amputees.

Prostheses commonly use EMG to detect signals from the user [4]. Therefore, the degrees of freedom the user can control is limited by the number of signals the user can generate. For users unable to generate an adequate amount of signals, an underactuated hand could be an advantageous alternative to the fully articulated prosthesis on the market.

Overall, commercially available prosthetic hands still are inferior to human hands with regards to degrees of freedom, amount of sensory feedback provided, and methods of classifying different grip patterns and motion [5]. Using a Reflex Takktile Hand and a Baxter robot, this project aims to close this gap by detecting and preventing object slippage based on tactile sensor data and classifying the rigidity of different objects. In addition, it attempts to reduce the deformation of objects during grasps. These goals have obvious applications in prosthesis and could improve the experiences of prosthetic hand users.

II. Related Works

There are several approaches that aim to address the aforementioned limitations of current prosthetic devices. The following are some of the approaches found in literature:

A. Slip detection and grasp methods

- Reference [6] detects slipping through two different methods. The first uses a piezoelectric polyvinylidenefluoride (PVDF) film to detect pressure changes. The second uses a strain gauge to measure static pressure. This method trains a neural network to be able to adjust the grasp according to the objects weight.
- Reference [7] developed a sensor to detect vibrations that occur from a slip from a regularly updated estimate of the coefficient of friction.
- Reference [8] studies the electrical resistance generated from shear deformation of pressure conductive rubber.
- Reference [9] uses the fluctuation of normal forces to determine slippage then FFT for fast computation, and an almost instantaneous reaction.
- Reference [10] developed a method to classify different types of slips and grasping strategies to combat them.
- Reference [11] tries to find an ideal finger placement for a grasp for a variety of objects while taking rigidity into account.
- Reference [12] focuses on the integral term of a sliding mode slip prevention controller. It then continues to show how this approach reduces deformity while grasping an object.
- Reference [13] aims to proactively prevent object slip in uncertain environment using a specialized controller.

B. Object classification

- Reference [14] uses neural nets and genetic algorithms to implement several features of active perception for autonomous agents.
- Reference [15] uses a low resolution intensity image from tactile sensors to identify objects using a bag-of-words approach. It uses this data to train a model to improve its classification.
- Reference [16] uses machine learning to identify objects using data from unplanned grasps with an underactuated hand with tactile sensors. The paper then uses parametric methods to estimate object properties.

III. Methods

The initial goal of the project was to detect object slippage and adjust the grip accordingly to prevent the object from slipping. This is accomplished using data given by the tactile sensors. The project evolved to detecting slipping through changes in tactile sensor data and naively adjusting grip force, and classifying the rigidity of an object.

A. Slip prevention

Slip prevention is separated into two sections: touch detection and slip prevention. Identifying when the fingers are touching an object is required to get an accurate starting point before the hand can adjust its grasp on the object. It also prevents object deformation by ensuring that the fingers only touch the object and do not apply significant force. This is done by monitoring if the pressure values on any of the sensors exceed a threshold of 1.0 (unitless) while the hand is closing on the object. The value 1.0 is used because it is the lowest detectable pressure value on the Takktile hand.

After detecting that the fingers have made contact with the object, the Takktile hand will begin the slip prevention stage. The first method that was attempted was a frequency based slip detection algorithm. When objects slip against a rubber surface, like the fingers of the Takktile hand, a frequency is created in pressure values. By taking the FFT of the time domain data, it is theoretically possibly to see a frequency with a higher amplitude when the object is slipping than when it is not slipping. Sample frequency data can be seen in Fig. 1 below. Though this method is promising and is independent of the orientation of the hand, the obtained frequency spectrums were inconclusive and showed no significant difference between when an object was slipping and when it was not.

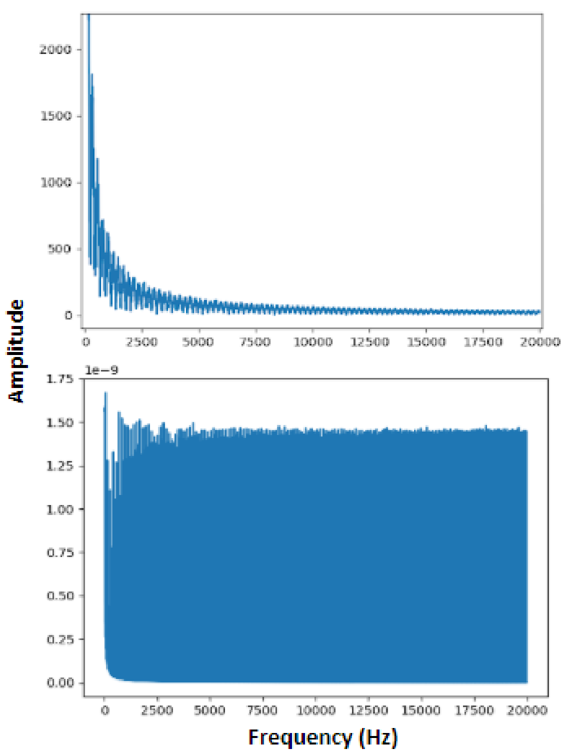

Fig. 1. Frequency spectrum examples

Instead, the real-time pressure values in the fingers were compared with previous pressure values at an average sampling rate of 250 kHz. If the difference between these two values exceeds a predefined threshold T, it is characterized as a slip. In response, the hand will tighten its grip on the object and will continue to tighten its grip until slipping is no longer detected. The lower the values of T, the faster the hand would respond to a slipping object. Example data from the tactile sensors can be seen below in Fig. 2.

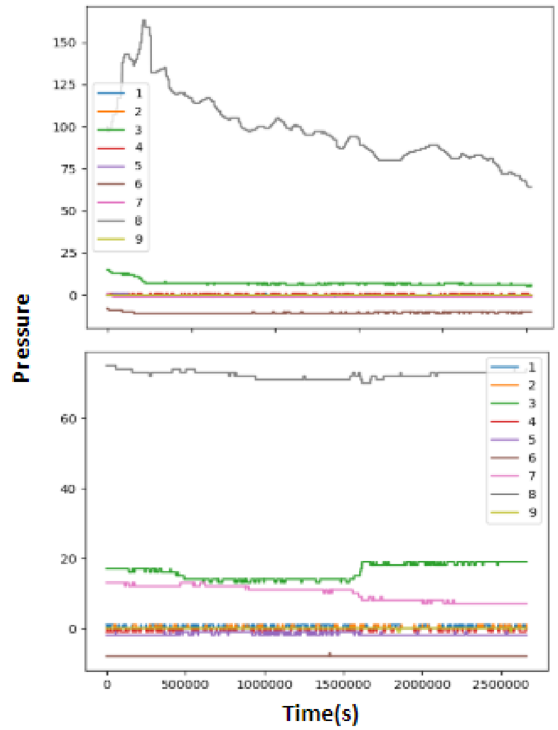

Fig. 2. Tactile sensor data for an object slipping (top) and an object not slipping (bottom)

B. Object classification

Object classification is implemented by comparing the change in motor load caused by an increase in grip force to a threshold. The steps are detailed as follows

1) The Takktile hand closes its fingers until a touch is detected as a value of 1.0 from the tactile sensor data, as described in the slip prevention method. The motor load for each finger is recorded as the initial motor load values.
2) The pressure threshold for the sensors increases from 1.0 to 50.0.
3) The fingers close until this new threshold of 50.0 is reached. The motor load for each finger is recorded as the final motor load values.
4) If the difference between the final and initial motor load values exceeds a predetermined threshold, the object is classified as deformable. Otherwise, the object is classified as rigid.

The threshold for motor load mentioned above was calculated by trial-and-error. This method is effectively monitoring how much work the motors have to do to produce a pressure value of 50.0. When the change in motor load is higher, this indicates that the fingers are able to close a significant amount after a touch was identified. Because the fingers are able to close, this would signify that the object is deformable. The fingers would not be able to close a significant amount if it were a rigid object.

IV. RESULTS

A. Experimental Setup

The experimental setup was divided into two parts: hand data collection and integration with Baxter. This project uses the Reflex Takktile hand, an underactuated, tendon driven, three-fingered robotic hand by RightHand Robotics. It has 9 tactile sensors on each finger: 5 tactile sensors on the proximal joint, and 4 tactile sensors on the distal joint. Grasps were executed using two opposing fingers and sensors in the proximal joints. The distal joint sensors were not used as they were not functioning correctly. The hand can be seen attached to Baxter in Fig. 3.

Fig. 3. Baxter with Reflex Takktile Hand attached to the arm

A custom 3D printed mount, shown below in Fig. 4, was made to attach the hand to Baxters arm. To perform repeated actions consistently on Baxter, a movement file was recorded. The file was replayed to test the slip prevention method on different objects. One hypothesis was that the grasp would not work for all objects as it is limited to two fingers. Another hypothesis was that slip prevention would not work for grasps at different orientations.

Fig. 4. Custom 3D printed Baxter mount for Reflex Takktile Hand

B. Slip Prevention

Cylindrical, spherical, rectangular, and complex shaped objects were used in this project. Slipping was consistently prevented with all the object types that we used. The hand was able to prevent slipping against someone pulling on the object in addition to slipping solely due to gravity. However, these grasps were heavily reliant on object orientation since a naive threshold based slip prevention algorithm was used rather than something more robust like the frequency based algorithm. For some shapes, increasing the grip will cause the object to slip out rather than securing it, such as a rigid sphere. In addition, the hand did not have a fast reaction time to objects slipping when the object was not in direct contact with a tactical sensor and was contacting the finger between two sensors.

C. Object Classification

The algorithm is able to classify objects consistently and accurately when the hand is gripping spherical or cylindrical objects. However, the classification system does not work as well for rigid objects with sharp edges like rectangular objects. These objects produced inaccurate results and misclassified objects. For example, a rectangular, rigid, lego piece was classified as deformable. During these grasps, the fingers would not completely surround the object after stopping at first contact. When the pressure threshold is increased, the fingers could continue to curve due to the complex shape regardless of its rigidity, subsequently increasing the motor load. This significant increase in load is similar to how a deformable object would perform. Since the classification is based on motor load, the system would incorrectly classify a sharp edged, rigid object as deformable. In general, the system is relatively accurate in classifying a wide array of objects with different shapes and densities, with the exception of a few geometries.

V. CONCLUSION

While the approach used in this paper proved to be efficient in preventing slipping and identifying the rigidity of complex objects, it could be improved in many ways. Due to several issues with the Reflex Takktile Hand, simplifications were made in the project design. First, the hand has functional sensors on only two out of three fingers. Therefore, all grasps were executed with two fingers and positional calibration had to be done manually, introducing human error. In addition, the tactile sensors on the distal joints of the hand are unreliable. In order to eliminate reliance on that data, grasps were executed using information from only the proximal sensors. In general, the tactile sensor data is noisy and the pressure sensitivity among different sensors is variable and inconsistent, which may be caused by unstable connections and wiring inside the hand.

Because grasps are executed using data only from proximal sensors, certain grasps cannot be executed properly, such as those that require the object to be held only by the distal joints. Moreover, the pressure values obtained from the sensors are limited to integer values, resulting in poor resolution for pressure frequency-based slip detection. Additionally, because the distal joints of the fingers are not actuated and are tendon-driven, they will not bend unless the proximal joints are in full contact with the object. This highly limits the types of grasps that are possible. Although the hand has the capability to change the angle between the two adjacent fingers, this was not utilized in the project because of the broken finger. Therefore, more complex actions such as executing a variety of grasps and reorienting an object while grasping were challenging to accomplish, given the state of the Takktile hand. Ideally, more information from the published hand state could be incorporated into the methods, but most unused data such as the raw and joint angles of the hand are unreliable and noisy.

Overall, the ideas explored in this project are a promising avenue for improving the experiences of prosthetic hand users. They can prevent objects from slipping out of a grasp without user intervention and can provide useful information about the characteristics of an object. However, several improvements must be made in order for the described methods to be robust and useful in the real world. First, it would be ideal to use three or more fingers of a hand to provide more degrees of freedom and make reorientation of an object possible, rather than relying only on a stronger grip force to combat slipping. Additionally, a more robust slip detection method is needed that is independent of the hand orientation. Possible approaches for this include developing a frequency based algorithm or using machine learning to classify different types of slips. Finally, the data from object classification could be used to modify the approach of a grip controller.

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