Deep Predictive Models for Active Slip Control

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Abstract— **We discuss a machine learning methodology for actively controlling slip, in order to increase robot dexterity. Leveraging recent insights in Deep Learning, we propose a Deep Predictive Model that uses tactile sensor information to reason about slip and its future influence on the manipulated object. We show in a set of experiments that this approach can be used to increase a robot's repertoire of skills.**

I. INTRODUCTION

Throughout our lifetime, we learn to delicately grasp, manipulate, and use a wide range of objects. Experience allows us to learn complex interactions with our enviorment such as increased dexterity in object manipulation. For example, we learn to actively use slip to our advantage, e.g., sliding, rotating, or shifting objects in-hand. However, in robotics, slip is often treated as a negative side effect that complicates interactions and should be actively avoided. Approaches to slip modeling and slip detection often aim at reducing or eliminating the effects of slip.

In this paper, we discuss how slip can be actively controlled to increase robot dexterity and capability. Previous approaches to slip control have focused on a theoretical analysis of the underlying forces, torques, and physical constraints. However, in practice, such models are often infeasible since they fail to represent the uncertainty and variability inherent in in-hand manipulation. We argue that a key component of success in active slip control is the acquisition of predictive models which anticipate the behavior of an object under different robot actions. Through repeated physical interactions, a robot arm learns to anticipate how its intended actions produce or reduce slip. This, in turn, leads to a change in the pose of the manipulated object. We propose a Deep Predictive Model (DPM) which can be used to effectively learn the relationship between robot actions, incurred slip, and future object poses. Finally, we also perform experiments and provide examples that show how this approach can be leveraged to achieve dexterous object manipulation with low-degree-of-freedom manipulators.

II. RELATED WORK

A large body of work on modeling slip has focused on prediction and prevention [1], [2] using tactile sensing. Other research focused on utilizing tactile information to classify linear or rotational slip by training a neural network to discriminate between these two types of slip [3]. Going beyond simple detection, slip has also been used

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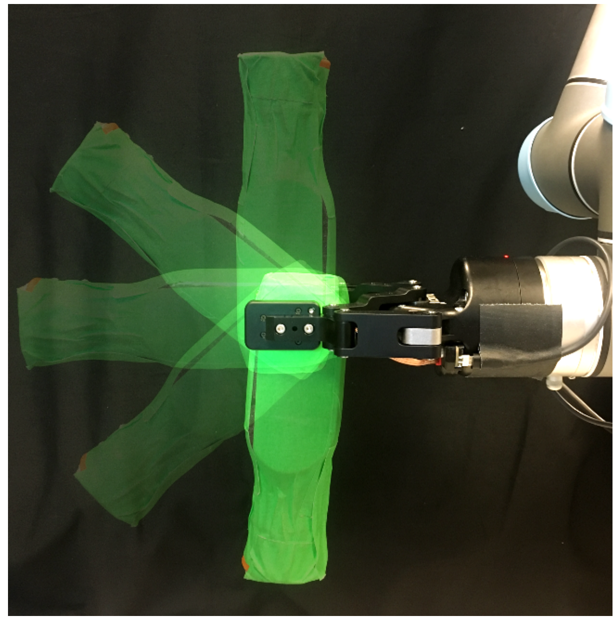

Fig. 1. Slip can be utilized to rotate an object to different target locations. This image shows five example target positions of the object. The robot is able to utilize slippage to rotate the object to the desired angle.

for dexterous in-hand manipulation of grasped objects [4]. An approach which only uses tactile sensing to rotate an object is described by [5]. A drawback of that approach, however, is that it still requires an external object to support the movement. In this work, slip is not considered as an undesired source of perturbation, but rather as an opportunity for dexterous manipulation. Compared to [4], the presented system is able to solely rely on tactile sensing for in-hand manipulation and does not need to use a supporting object as in [5]. In addition, no analytical model of the underlying mechanics and forces is needed.

III. METHODOLOGY

We use the Robotiq adaptive two finger gripper, equipped with a tactile sensor on each finger [6]. Each of the two sensors has a four by seven matrix, allowing it to measure absolute pressure values. In addition to these 56 static tactile sensors, one dynamic sensor is available in each finger.

When utilizing slip to re-orient an object in the gripper, a robot needs to predict the outcome of its actions on the pose of the manipulated object. For this purpose, a deep neural network is trained to predict the absolute rotation of the object at run time. More specifically, we train a fully connected network with five hidden layers, as shown in figure 2, to act as a DPM. The network structure was determined

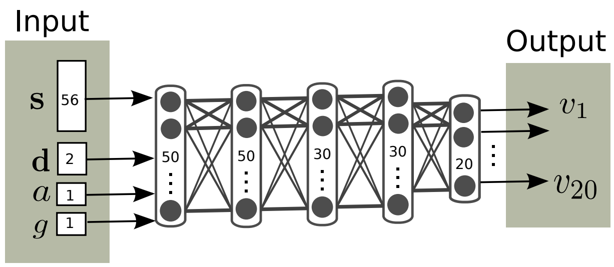

Fig. 2. Schematic visualization of the deep predictive model proposed in this work.

empirically by running a grid search. Once trained, the DPM generates an estimate of the object's future orientation for the next $N = 20$ time steps. Predictions are generated based on the current static and dynamic tactile data, gripper closing angle and rotation of the UR5's end-effector with respect to the ground. Formally, the prediction process can be represented by the following equation:

$$f(\mathbf{s}, \mathbf{d}, a, g) \rightarrow \mathbf{v} \tag{1}$$

where $\mathbf{s} \in \mathbb{R}^{56}$ is the vector of static tactile sensor activations, $\mathbf{d} \in \mathbb{R}^2$ is the vector of dynamic tactile sensor values, a is the angle of the end-effector, and g is the value describing how far the gripper is closed. The output $\mathbf{v}$ is a vector containing the absolute rotations for the next twenty time steps $\{v_t, \cdots, v_{t+20}\}$, where one time step is set to a hundredth of a second. It is important to note, that it is not necessary to employ any recurrent layers in this network since the dynamic tactile sensing is included in the data. This ensures that the network is still able to infer latent features about the rate of change without resorting to recurrent layers. The adaptive moment estimation (Adam) [7] method is used for training, with a learning rate of 0.001. Mean squared error is utilized as the loss function.

For training purposes, the ground truth rotation is measured with an acceleration sensor embedded inside of the object. During training, labels for the absolute rotations were acquired by mapping the values from the accelerometer to the angle of the object with respect to the floor. To train the network, 100 demonstrations of a 180 degree slip were recorded, resulting in 19,000 samples after removing all samples with less then zero or more than 180 degrees of rotation. Furthermore, all data points are normalized before they are used in the training process. To accurately represent the movement, all data points are collected with a rate of 100Hz, resulting in an average resolution of one sample per degree. These data points were randomly divided into 70% training, 20% validation and 10% testing. To initiate slip during training, the gripper was given an initial rotation of ten degrees. After reaching the start position, the gripper was slightly opened to allow the object to slip. The demonstration ends as soon as the object reaches a total rotation of more than 180 degrees. One training example is roughly illustrated in figure 1 where the values mentioned above are collected while the object is rotating.

At run time, the predictions are used to close the gripper at the right moment such that the object is stopped from further slippage in the desired position. A benefit of predicting multiple steps into the future is the ability to select the correct amount of look ahead to resolve any network and control latencies.

IV. EVALUATION

Using the previously mentioned controller that produces the desired rotations as seen in figure 1, the DPM acheives an accuracy within ± 10 degrees of error for 80% of the trials. In addition, 50% of the trials are within an error margin of ± 5 degrees. Furthermore, the same DPM was used in a dynamic experiment which introduced centrifugal forces and acceleration to initialize the slip of the object. The dynamic task was to transport an object from one location to another while rotating it from a vertical to a horizontal position. Multiple trials showed that the task can be accomplished successfully in 70% of the attempts.

V. CONCLUSION

In this paper, a novel approach for dexterous manipulation is presented by leveraging slippage to rotate an object in-hand. Experiments support the feasibility of this approach in real-world applications and indicate that the approach can increase a robot's repertoire of skill. Especially during fast movements where an object is more likely to slip due to acceleration or centrifugal forces, the presented approach can effectively leverage these predictions to rotate the object to a desired position.

Future work will focus on using a dynamic controller to determine which predicted time step best compensates for latencies occurring in the pipeline to increase the overall accuracy of the system. Additionally, the model needs to be evaluated with different objects.

REFERENCES

[1] F. Veiga, H. van Hoof, J. Peters, and T. Hermans, "Stabilizing novel objects by learning to predict tactile slip," in *2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 5065–5072, Sept 2015.

[2] Y. Ma, Y. Huang, L. Mao, P. Liu, C. Liu, and Y. Ge, "Pre-sliding detection in robot hand grasping based on slip-tactile sensor," in *2015 IEEE International Conference on Robotics and Biomimetics (ROBIO)*, pp. 2603–2608, Dec 2015.

[3] Z. Su, K. Hausman, Y. Chebotar, A. Molchanov, G. E. Loeb, G. S. Sukhatme, and S. Schaal, "Force estimation and slip detection/classification for grip control using a biomimetic tactile sensor," in *2015 IEEE-RAS 15th International Conference on Humanoid Robots (Humanoids)*, pp. 297–303, Nov 2015.

[4] C. A. Jara, J. Pomares, F. A. Candelas, and F. Torres, "Control framework for dexterous manipulation using dynamic visual servoing and tactile sensors feedback," *Sensors*, vol. 14, no. 1, pp. 1787–1804, 2014.

[5] H. van Hoof, T. Hermans, G. Neumann, and J. Peters, "Learning robot in-hand manipulation with tactile features," in *2015 IEEE-RAS 15th International Conference on Humanoid Robots (Humanoids)*, pp. 121–127, Nov 2015.

[6] T.-H.-L. Le, A. Maslyczyk, J.-P. Roberge, and V. Duchaine, "A highly sensitive multimodal capacitive tactile sensor," *International Conference on Robotics and Automation*, 2017.

[7] D. Kingma and J. Ba, "Adam: A method for stochastic optimization," *International Conference on Learning Representations*, 2015.