Active Slip Control for In-Hand Object Manipulation using Deep Predictive Models

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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.

Concept
Experience allows us to learn complex interactions with our environment such as increased dexterity in object manipulation by leveraging slip. In robotics, slip is often treated as a negative side effect that complicates interactions and should be actively avoided. In this work, we discuss how slip can be actively controlled to increase robot dexterity and capability like sliding, rotating, or shifting objects in-hand. 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.

Approach
We use the Robotiq adaptive two-finger gripper, equipped with a tactile sensor on each finger [1]. As robotic platform, the UR5 is used.

The deep predictive model consists of a fully connected neural network with five hidden layers, as shown in the figure above. Formally, the prediction process can be represented by the following equation:

\[ f(s, d, a, g) \rightarrow v \]  \hspace{1cm} (1)

where \( s \in \mathbb{R}^{56} \) is the vector of static tactile sensor activations, \( d \in \mathbb{R}^2 \) is the vector of dynamic tactile sensor values [2], \( a \) is the angle of the end-effector, and \( g \) is the value describing how far the gripper is closed.

The output \( v \) is a vector containing the absolute rotations for the next twenty time steps \( \{v_1, \ldots, v_{20}\} \).

Further components of this approach:
- Predicting multiple future time steps can be used to compensate for latencies
- Ground truth data are labeled with an accelerometer within the training object
- Slip can be learned from \( \sim 100 \) demonstrations
- In total, \( \sim 19,000 \) training examples where created

Experimental Results
The first experiment has the goal to stop the object in the desired orientation. For this purpose, four target angles where selected as seen in the diagram above. Each target position was approached 25 times and the difference between the goal and actual angle was recorded.

In the second experiment, the robot utilized slippage which is induced by acceleration and/or centrifugal forces. Two examples of these interactions can be seen in the figure above. For the second task, the robot had to rotate the bottle for 90 degrees while moving it on a table. Experiments showed that this task can be accomplished with a success rate of 80%.

Conclusion
We present a novel approach for dexterous manipulation which leverages slippage to rotate an object in-hand. First experiments showed that the approach can increase a robot’s repertoire of skill during static and dynamic tasks.

Future work:
- The method needs to be evaluated with different objects: Different mass distribution; changing center of mass.
- A dynamic controller needs to be created to determine which predicted time step best compensates for latencies occurring in the pipeline.

References