Friction Variability and Sensing Capabilities for Data-Driven Slip Detection

Zixi Liu$^1$ and Robert D. Howe$^{1,2}$

Abstract—Reliable slip detection enables stable grasping in unstructured environments and controlled motion in manipulation. The coefficient of friction is highly variable, and often non-linear, depending on many factors such as load, contact velocity, material, etc. This variability makes slip prediction challenging. Here we characterize the range of variability for the coefficient of friction with respect to load and contact velocity. We perform grasping experiments with external forces causing instabilities and slip. From the experiment data, we train a machine learning model that achieves $95\% f_1$ score and an optimization-based single-value coefficient of friction threshold baseline model with $f_1$ score of $86\%$. Furthermore, we perform an ablation study by re-training while removing one sensing capability at a time. The results show that normal and tangential force are both key to successful slip detection. This also shows the trade-offs and limitations between high sensing capabilities and cost for the robot's ability to detect slip and friction.

I. INTRODUCTION

Slip detection is a key challenge for stable grasping and manipulation in unstructured environments as well as for controlled slipping. Coulomb’s Law of friction can be used to detect slip, but requires an accurate estimate of the coefficient of friction, $\mu$. When the estimate is too conservative, it results in excessive force causing instability, damage to the object, or failure in controlled sliding such as swiping on a tablet; when too relaxed, it will result in unstable grasps. Typically, the coefficient of friction is estimated as a constant value from literature. The actual values, however, are often variable. Modern robotic hands often have rubber or other (semi-)soft material for easier grip; these materials have particularly large variability in the coefficient of friction, depending on many factors such as the materials in contact, load, how long it has been slipping, contact velocity, and deformation [1][2].

Recently, much research has focused on machine learning (ML) methods for slip detection [3], [4], [5], [6], [7], [8], [9], [10] with $f_1$ score ranging from $72\%$ to $92\%$. This work investigates the range of variability in the coefficient of friction $\mu$; evaluates an optimization-based baseline model assuming a constant $\mu$; trains a ML model for greatly improved slip detection; and performs an ablation study to investigate the importance of different sensing capabilities. The ML model achieves an $f_1$-score of $95\%$ compared to the baseline $86\%$. Both normal and tangential force are key to successful classification.

The experiments use a modified tendon-driven three-fingered robot hand (Reflex Hand, RightHand Robotics) with custom-designed fingers. Each fingertip is equipped with a high precision force/torque sensor (ATI Nano17. Resolution: $1/160$ N, $1/32$ Nmm, $500$Hz). A hemispherical fingertip with a solid $17mm$ inner layer (Stratasys Vero White) and a $3mm$ silicone coating (Smooth-on Dragon Skin 30) is mounted to the force/torque sensor. The hand is mounted on a robot arm (Universal Robot UR-5). A high precision optical tracking system (Atracsys Fusion Track 500. Resolution: $0.090$ mm RMS, $330$Hz) measures the pose of each fingertip the grasped object. For the object, we 3D-printed a $84mm$ cube with fiducials mounted on the front face for precise pose tracking. The sides of the cube are treated with sandable primer (Rust-Oleum 249418A2 Spray) to provide a well-defined surface.

In this work, we collected two types of data: (1) an human operator holds the robot finger by hand, slides and rolls on a smooth surface (treated with the same primer) while varying load ($0\sim10N$) and slipping speed ($0\sim100$ mm/s) to characterize the variability in the coefficient of friction (Figure 1-A). (2) First, the robot hand grasps the object, then lifts and securely holds it. Then, a human operator pushes the object at the corners and edges, causing the object to move in the robot hand without dropping. The external forces are varied in this procedure such that disturbances produce both gradual slow slip as well as sudden movement (Figure 1-B). Figure 1-C shows typical data in the 2nd experiment. The ground truth is labeled based on contact velocity, shown in blue-shading. A set of 6 trials is collected, each lasting approximately 1

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$^1$Zixi Liu is with School of Engineering and Applied Sciences, Harvard University, Cambridge USA zixilu@g.harvard.edu

$^2$Robert Howe is with $^1$School of Engineering and Applied Sciences, Harvard University, Cambridge, USA, and $^2$RightHand Robotics, Inc., 237 Washington St, Somerville, MA 02143 USA. howe@seas.harvard.edu
### III. RESULTS

A. **ML significantly improves slip detection compared to single-value threshold optimization**

Figure 2-A shows that ML improves slip detection performance significantly with a f1-score of 95.06% compared to baseline 86.30%. Although the recall values are very similar, ML model is able to improve precision significantly from 78.24% to 94.58%. This suggests that the baseline model is overly conservative and has a high false-alarm rate. Figure 2-C shows that the coefficient of friction increases with respect to contact velocity and decreases with respect to normal force, with a wide range from 1 to 1.65. Figure 2-B shows the optimization results for the baseline model. The highest f1 score is achieved at a coefficient of friction 1.12 with a f1 score of 86.37%.

#### TABLE I

<table>
<thead>
<tr>
<th>Sensing Capabilities</th>
<th>F1 Score</th>
<th>Precision</th>
<th>Recall</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1) Full ML</td>
<td>95.06%</td>
<td>94.58%</td>
<td>95.53%</td>
<td>98.72%</td>
</tr>
<tr>
<td>2) No history</td>
<td>94.07%</td>
<td>92.89%</td>
<td>95.27%</td>
<td>98.45%</td>
</tr>
<tr>
<td>3) No $v_f$</td>
<td>93.73%</td>
<td>92.15%</td>
<td>95.36%</td>
<td>98.35%</td>
</tr>
<tr>
<td>4) No raw data</td>
<td>92.59%</td>
<td>90.91%</td>
<td>94.34%</td>
<td>98.05%</td>
</tr>
<tr>
<td>5) No $F_{xyz}$</td>
<td>92.54%</td>
<td>91.07%</td>
<td>94.06%</td>
<td>98.04%</td>
</tr>
<tr>
<td>6) Implicit $F_{t}$</td>
<td>84.65%</td>
<td>84.24%</td>
<td>85.06%</td>
<td>96.01%</td>
</tr>
<tr>
<td>7) No $F_{n}$</td>
<td>74.24%</td>
<td>74.01%</td>
<td>74.48%</td>
<td>93.32%</td>
</tr>
<tr>
<td>8) No $F_{t}$</td>
<td>7.41%</td>
<td>43.17%</td>
<td>4.05%</td>
<td>96.91%</td>
</tr>
<tr>
<td>Baseline</td>
<td>86.37%</td>
<td>78.24%</td>
<td>96.40%</td>
<td>97.07%</td>
</tr>
</tbody>
</table>

### IV. DISCUSSION

Effective grasping and manipulation depends on slip detection. As demonstrated in this work, friction is a complex phenomenon. The coefficient of friction varies significantly with respect to load and slip velocity (Figure 2-C), materials, temperature, deformation, etc.[1] [2], and cannot be reduced to a single constant. Therefore, slip prediction based on assumptions of a constant value for the coefficient of friction will be unreliable (Figure 2). Given the complexity of friction, here we adopt a ML method for slip detection and show significant improvement to a f1 score of 95.06% vs. an optimized single-value threshold-based baseline model with a f1 score of 86.37%. From the feature ablation study, we found that normal and tangential force is crucial in successful slip detection. These findings motivates development of robot hands with such sensing capabilities. Although the scope of this work is limited to a single material, the fact that the ML model was able to train very well with a small dataset suggests that it may be possible to use tactile sensors to slide against the object surface at the beginning of the grasping/manipulation process to update a friction model. This is similar to how human processes tactile information from mechanoreceptors to quickly estimate friction properties during the first second in contact with an object. For future work, we aim to evaluate different materials as well as object surface geometries to develop slip detection models that can extend to everyday objects.
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REFERENCES