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Friction Variability and Sensing Capabilities for Data-Driven Slip Detection

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Abstract— **Reliable slip detection enables stable grasping in unstructured environments and controlled motion in manipulation. The coefficient of friction is highly variable, and often nonlinear, 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% f1 score and an optimization-based single-value coefficient of friction threshold baseline model with f1 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, μ. 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 f1 score ranging from 72% to 92%.

This work investigates the range of variability in the coefficient of friction μ; evaluates an optimization-based baseline model assuming a constant μ; 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 F1-score of 95% compared to the baseline 86%. Both normal and tangential force are key to successful classification.

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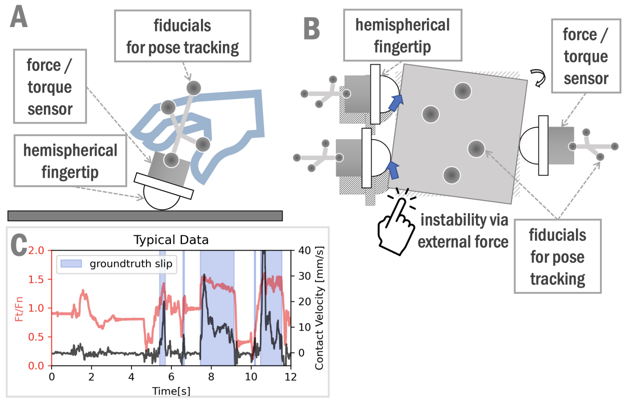

Fig. 1. (A) Hand-held experiment (B) Experimental setup: external force causing instability. (C) Typical data in the experiments. Note the variability of $\mu = F_t/F_n$ during slip.

II. METHODS

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, 500Hz). 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, 330Hz) 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$\sim$10N) and slipping speed (0$\sim$100 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

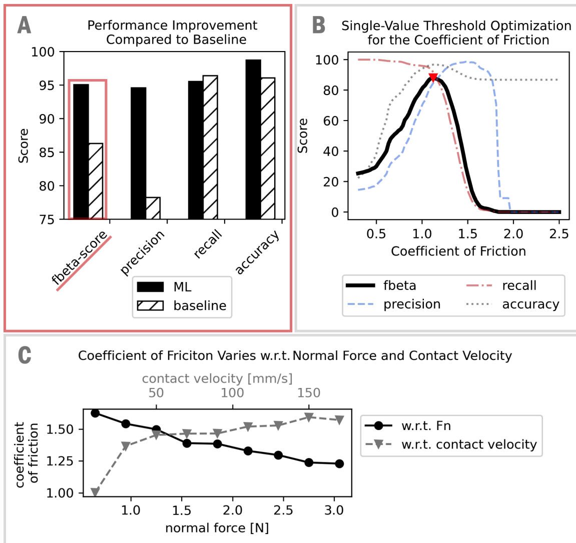

Fig. 2. Experimental Results

minute, containing 10-15 external disturbance events. Data is divided into training and testing sets evenly.

Here we use an optimization-based single-value coefficient of friction threshold method for a baseline. We sweep from $\mu = 0.3$ to 2.5. For each sample, if Ft/Fn is higher than this value, the instance is labeled "slip" and if lower, "non-slip". The results are compared to the ground truth and the optimal μ is determined by the highest f1 score.

For the ML classifier, we use the Random Forest Classifier (Scikit-Learn) with a balanced weight-class. Features include the following: normal force Fn, tangential force Ft, raw sensor force readings Fxyz, raw sensor torque reading Tx, contact velocity on the fingertip v_f (i.e. how fast the contact point is moving on the fingertip), δ Fn (single-step time difference), δ Ft, Ft/Fn, accumulated values for Ft/Fn in the past 5 timestamps, and that for the past 15 timestamps. To understand the importance of sensing capabilities, we did an ablation study removing one sensing capability a time:

Sensing Capabilities	Features/Inputs
1) Full ML	All 12 features
2) No history	Fn, Ft, Fxyz, Tx, v_f, δ Fn, δ Ft, Ft/Fn
3) No v_f	Fn, Ft, Fxyz, Tx, δ Fn, δ Ft, Ft/Fn
4) No raw data	Fn, Ft, v_f, δ Fn, δ Ft, Ft/Fn
5) Fn Ft only	Fn, Ft, δ Fn, δ Ft, Ft/Fn
6) Implicit Ft	Fn, Fxyz, Tx, v_f, δ Fn
7) No Fn	Ft, v_f, δ Ft
8) No Ft	Fn, v_f, δ Fn
Baseline	Fn, Ft

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 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 coefficient of friction 1.12 with a f1 score of 86.37%.

Sensing Capabilities	F1 Score	Precision	Recall	Accuracy
1) Full ML	95.06%	94.58%	95.53%	98.72%
2) No history	94.07%	92.89%	95.27%	98.45%
3) No v_f	93.73%	92.15%	95.36%	98.35%
4) Fn Ft only	92.59%	90.91%	94.34%	98.05%
5) No raw data	92.54%	91.07%	94.06%	98.04%
6) Implicit Ft	84.65%	84.24%	85.06%	96.01%
7) No Fn	74.24%	74.01%	74.48%	93.32%
8) No Ft	7.41%	43.17%	4.05%	86.91%
Baseline	86.37%	78.24%	96.40%	96.07%

TABLE I

B. Normal and tangential forces are key in slip detection

As shown in Table I, history, contact velocity on the fingertip v_f, and raw data all play a small role and marginally improve the overall f1 score but are important to get f1 score as high as possible. However, when Ft is not explicitly calculated, even with indirect information, the overall f1 score drops drastically to 85%, on par with the baseline(calculated with explicit Ft). This finding shows that explicit tangential force plays an important role especially when the dataset is small. When Fn is unavailable, the f1 score drops to 74.24%, indicating that Ft alone is not sufficient to accurately classify slip. When Ft is unavailable, most sample were classified as non-slip and the overall f1 score is only 7.41%, suggesting that Fn alone also is insufficient to train a successful model.

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 mechano-receptors 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

[1] N. K. Myshkin and D. V. Tkachuk, "Polymer Tribology Fundamentals," in *Encyclopedia of Tribology*. Springer US, 2013, pp. 2614–2619.

[2] Z. Liu and R. D. Howe, "Overlooked Variables in Compliant Grasping and Manipulation," in *ICRA 2022 Workshop: Compliant Robot Manipulation: Challenges and New Opportunities*, 2022.

[3] A. Garcia-Garcia, S. Orts-Escolano, and J. Garcia-Rodriguez, "TactileGCN: A Graph Convolutional Network for Predicting Grasp Stability with Tactile Sensors; TactileGCN: A Graph Convolutional Network for Predicting Grasp Stability with Tactile Sensors," *2019 International Joint Conference on Neural Networks (IJCNN)*, 2019. [Online]. Available: http://www.ieee.org/publications

[4] Li Luxuan, F. Sun, Z. Huang, C. Yang, and M. Jing, "Learning to detect slip for stable grasping," in *IEEE International Conference on Robotics and Biomimetics*, 2017.

[5] J. W. James and N. F. Lepora, "Slip detection for grasp stabilization with a multifingered tactile robot hand," *IEEE Transactions on Robotics*, vol. 37, no. 2, pp. 506–519, 4 2021.

[6] B. S. Zapata-Impata, P. Gil, and F. Torres, "Learning Spatio temporal tactile features with a convLSTM for the direction of slip detection," *Sensors (Switzerland)*, vol. 19, no. 3, 2 2019.

[7] F. Veiga, J. Peters, and T. Hermans, "Grip Stabilization of Novel Objects Using Slip Prediction," *IEEE Transactions on Haptics*, vol. 11, no. 4, pp. 531–542, 10 2018.

[8] 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 *IEEE-RAS International Conference on Humanoid Robots*, vol. 2015-December. IEEE Computer Society, 12 2015, pp. 297–303.

[9] F. Veiga, H. Van Hoof, J. Peters, and T. Hermans, "Stabilizing Novel Objects by Learning to Predict Tactile Slip," Tech. Rep.

[10] Q. Feng, Z. Chen, J. Deng, C. Gao, J. Zhang, and A. Knoll, *Center-of-Mass-based Robust Grasp Planning for Unknown Objects Using Tactile-Visual Sensors; Center-of-Mass-based Robust Grasp Planning for Unknown Objects Using Tactile-Visual Sensors*, 2020.