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M. Skouras and H. Wang (Editors) *Poster*

Data-driven Friction for Real-time Applications

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Abstract

We present a novel data-driven approach for simulating friction between rigid bodies that captures the rich diversity of frictional behaviors that arises due to the complex interactions of micro-asperities of different surfaces. Rather than performing detailed simulations with expensive collision detection, we parameterize our friction model based on aggregate features of pairs of surfaces, such as the distribution of normals from each surfaces, which may be easily computed from a texture-based embedding. Our data-driven model is constructed by conducting real-world planar pushing experiments that capture the friction behavior of many different material pairs, and we then fit this data using a Gaussian process (GP). The trained GP model is then evaluated in a real-time simulation and used to update the limit surface used by the contact solver.

CCS Concepts

• ***Computing methodologies*** $\rightarrow$ ***Modeling and simulation;***

1. Introduction

Coulomb friction is the standard friction model used in computer animation. The model describes a relationship between the normal contact force and the planar friction force that is non-linear. In simulators that target real-time performance, this non-linear relationship is linearized [AEF22]. This simplification in the model makes major gains in computational performance at the detriment of losing complex friction interactions that would arise from the material surface interactions. As such, many simulators fail to capture the plausible anisotropic friction interactions that materials such as wood or brushed aluminium would exhibit in certain circumstances.

There has been some work in computer graphics that focuses on developing more complex that go beyond the expressiveness that is possible with the traditional Coulomb model. For example, Erleben et al. [EMAK20] developed a simple interpolation model based on principle material directions that is able to capture direction based friction responses that depends on the relative alignment of the surfaces. Andrews et al. [ANEK21] also account for the relative direction and orientation of the surfaces, but additionally take into account the meso-geometry interactions using a ploughing model. We build on this latest work by continuing to focus on geometric surface interactions, but take a data-driven approach that learns frictional behavior from a dataset of real-world surfaces collected using a custom capture pipeline.

2. Overview

The capture pipeline is broken down into three main parts. First, the data gathering and processing where we perform planar pushing experiments using pairs of different materials. We further acquire surface scans of the materials at the meso-scale level. Second, a modeling stage trains a GP using the collected push force and geometry information. The inputs of the GP model are the relative pushing direction and aggregate features computed from the surface normal maps, and the output is a friction coefficient defining the limit surface for a given push direction and relative orientation of the surfaces. Finally, once this GP is trained, it can be loaded in a standard simulator and queried by the numerical solver algorithm when information about the friction limits is needed.

3. Data Gathering and Processing

Our planar pushing experiment setup consists of a fixed 6"$\times$6" bottom surface and a 3"$\times$3" top object. The top object is pushed by a human operator until it begins to slide against the bottom surface. In addition, the top object is able to carry various loads as well as the ability to attach various sheets of materials at the bottom, giving the ability to test various material pair interactions. We use an ATI Nano25 F/T sensor which is mounted on a probe that is handled by the human operator. We also capture the motion of the probe and the top moving object throughout the experiment by using a motion capture setup. Furthermore, to get data on the surface geometry of the materials, we scan each material using a GelSight Benchtop scanner that is able to capture a small sample area, which we export as a normal map. Here we assume that the surface is homogeneous, i.e., the scan sample is a good representation of the entire material's surface geometry.

In a Coulomb based friction model, the friction behavior is characterized by the friction limit surface. That is, the boundary be-

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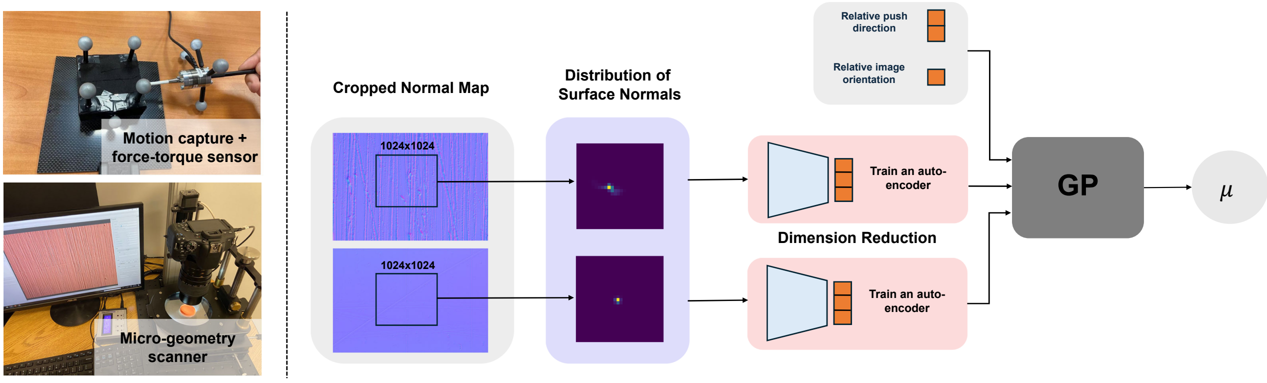

Figure 1: ***Left****: The experimental setup showing the planar push apparatus with motion capture and forces sensors (top) and the micro-geometry scanner (bottom).* ***Right****: We show the process of learning the coefficient of friction given the probe push direction, the relative orientation of the two surfaces, and encodings of the material pair's distribution of normal vectors histograms. Here we've used a scan of brushed nylon (top) and smooth nylon (bottom).*

tween static and dynamic friction. As such, we look in our data for instants where the object started moving and record the corresponding force.

Our dataset consists of frictional and surface data from various materials, such as wood, nylon, and "brushed" nylon, i.e. nylon that was scratched in one direction to create grains along the surface.

4. Modeling

The modeling pipeline is summarized in Figure 1. As previously mentioned, a Gaussian process is used for fitting the data. GPs have the advantage of working well with a small number of data points as well as with noisy data, as long as the noise follows a Gaussian distribution. It also has the advantage of being fast to train, unlike neural nets. We use the standard radial basis functions as kernel.

The acquire geometry scans are of very high resolution. We reduce the resolution of the data by taking a crop of the scan. It is important that the crop is large enough to be able to capture the general geometric patterns of the surface. To avoid training with very highly dimensional and noisy data, we further reduce the dimension by extracting a 2D histogram distribution of the normals of the scan. We finally reduce the dimensions again finding a three value latent space representation of the 2D histogram using an auto-encoder.

5. Results and Discussion

We train the GP with four different experiments comprised of combinations of nylon, wood, and brushed nylon. The total dataset comprises of 2780 data points and we train the GP for 800 epochs. Figure 2 shows the output of the trained model when evaluated on one of the experiments. Note the smoothing effect that the GP has as it does not capture the low-valued outliers. Future work will address this artefact and extend the GP model to handle this noisy, which we believes stems from the stochastic nature of friction.

One limitation of our approach is that the data we collect only focuses on specific regime of materials. Real-world friction depends

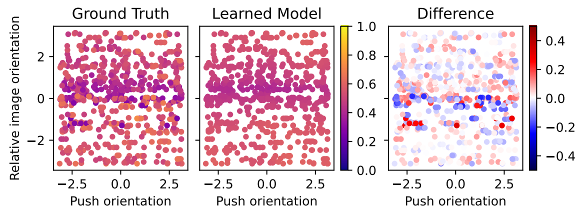

Figure 2: *We evaluate the model with one of the training experiments comprising of pushing smooth nylon on a brushed nylon surface. The coefficient of friction (color) with respect to the planar push orientation and the relative orientation of the two surfaces is plotted. Axes are in radians.*

on a multitude of complex phenomena, such as temperature, load, wear of the material, sheer forces acting upon the object, micro-deformations at the surface, and even molecular interactions. One potential future direction would be to use a high resolution, non real-time simulation of rigid body planar pushing to collect training data. This would give additional control over the surface geometry, as well as adding further modeling capabilities as mentioned above.

References

[AEF22] ANDREWS S., ERLEBEN K., FERGUSON Z.: Contact and friction simulation for computer graphics. In *ACM SIGGRAPH 2022 Courses* (New York, NY, USA, 2022), SIGGRAPH '22, Association for Computing Machinery. doi:10.1145/3532720.3535640. 1

[ANEK21] ANDREWS S., NASSIF L., ERLEBEN K., KRY P. G.: Coupling friction with visual appearance. *Proc. ACM Comput. Graph. Interact. Tech. 4*, 3 (sep 2021). doi:10.1145/3480138. 1

[EMAK20] ERLEBEN K., MACKLIN M., ANDREWS S., KRY P. G.: The matchstick model for anisotropic friction cones. *Computer Graphics Forum 39*, 1 (2020), 450–461. doi:https://doi.org/10.1111/cgf.13885. 1

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