Identification and validation of impact models

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<u>Summary</u>. Predicting the outcome of an impact event is of high importance for proper execution of many robotic tasks. Rigid-body contact models are extensively used in planning and control due to their simplicity and computational efficiency. However, there exists little literature that shows a comparison and verification of these models with real-life experiments, and it is therefore unclear how well these models approximate frictional impact events. In this study, we formulate an identification approach to find the parameters of commonly used contact, friction, and impact models using an experimentally obtained data-set of impact events using a single rigid-body, where the focus lies specifically on spatial frictional impact events. In future work, we will measure, using the identified parameters, the performance of the used models in terms of long-horizon prediction performance by comparing simulated and measured rest poses of a rigid-body tossed on a surface.

Introduction

Many robotic tasks rely on accurate dynamical models of the robot as well as models of the interactions the robot has with its environment or the object it is handling. Detailed understanding of the frictional impact events that occur when dynamic manipulation tasks are executed are important for proper task execution. Quantitative modeling these nonsmooth dynamics related to such stick/slip transitions and impacts events is highly challenging. Various models have been presented in literature and in this study the focus lies on rigid contact models, where the Newton-Euler equations of motion are coupled with ideal unilateral contact constraints (Signorini's contact law), Newton's impact law, and Coulomb's friction law [1, 2]. Newton's and Coulomb's law rely on parameters known as the coefficient of restitution (COR) and coefficient of friction (COF), denoted by e_N and μ , respectively. Identifying these parameters from an experimental data-set requires expertise in both mechanics and optimization, and ultimately gives an approximation of the real physical behavior of the object, as also addressed in [3]. In this study, the goal is to determine to what extent rigid-body dynamics can be used to describe real world physical behavior. More specifically, we focus on a single body impacting a surface and compare measurements with rigid-body simulations to quantify the predictive capacity of these models. The main contribution is that our focus lies on spatial frictional impact events, instead of the planar impact events considered in, for example, [4, 5].

Obtaining impact events from experiments

An experimentally obtained data-set is used to estimate the COR and COF for an uniformly filled carton box impacting a surface, which in our case is the box shown in Figure 1b. Experiments are executed on a robotic setup using a OptiTrack motion capture system to record at 360fps the poses of rigid-objects with sub-millimeter accuracy, see Figure 1a for a picture of the setup. This setup is representing a typical scenario in a logistic application, which sets the context of the project in which the experiments were executed ¹. From the tracking data it is possible to extract the exact configuration of the box and the surface with which the object is impacting and we compute the velocity of the box using a central differencing scheme. Figure 2 shows the twist of the box around a single impact event (happening at the time instance t = 0, where the time is normalized around the impact time), where Figure 2a shows the linear velocity component and Figure 2b shows the angular velocity (at t = -1) and post-impact velocity (at t = 1), which will serve as the basis for the identification of the impact map.

Parameter Identification based on post-impact velocity comparison

A total of 129 impact events where collected experimentally, from which we determine the pre- and post-impact velocity of the rigid body, where the pre-impact velocity serves as the input to a model-based simulation. We then let the simulator compute the post-impact velocity of the rigid-body given a certain value for e_N and μ and we compare the simulated post-impact velocity $\tilde{\mathbf{v}}^+$ to the post-impact velocity computed from the measurement data \mathbf{v}^+ . By performing a gridbased search over the parameter space, we are then able to find the optimum parameters. Mathematically, we define the optimization problem as

$$(\mu^*, e_N^*) = \underset{\mu, e_N, e_T}{\operatorname{arg\,min}} \frac{1}{N} \sum_{k=1}^N \left(\left\| \operatorname{diag}(\mathbf{w}) \left(\mathbf{v}^+ - \tilde{\mathbf{v}}^+ \right) \right\| \right)_k, \tag{1}$$

s.t.
$$0 \le \mu \le \mu_s, \quad 0 \le e_N \le 1,$$
 (2)

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Figure 1: Experimental setup. Picture of the lab (a) and picture of the carton box (b).



Figure 2: Linear and angular hybrid velocities obtained from measurements. Fitted hybrid velocities shown as black dotted lines.



Figure 3: Sum of computed costs from all 129 combined impact events as obtained for simulations with different parameters (a) and evolution of parameter values for increasing number of impact events (b).

where the simulated post-impact velocity $\tilde{\mathbf{v}}^+$ is a function of the pre-impact pose and velocity and the chosen values for the parameters μ and e_N . Furthermore, in (1), N denotes the total number of impact events and \mathbf{w} is a weighting vector. As a result, the sum of all computed costs can be seen in Figure 3a, while Figure 3b shows the convergence behavior of the values e_N and μ as function of the number of impact events, with the optimum values found as $\mu = 0.48$ and $e_N = 0.38$.

Conclusions

In this study, an experimentally obtained data-set is used for parameter identification of a nonsmooth impact model by comparing post-impact velocities from measurements to those obtained from simulations in a cost function. In future work, the identified parameters will be used for the long-horizon prediction of the objects state and the performance of the nonsmooth models with be measured by comparing simulation results to experimental data.

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