Data Collection for Screwdriving

Reuben M. Aronson*, Ankit Bhatia†, Zhenzhong Jia‡, and Matthew T. Mason§
Robotics Institute
Carnegie Mellon University, Pittsburgh, Pennsylvania, 15213
*Email: rmaronson@cmu.edu
†Email: ankitb@cmu.edu
‡Email: zhenzjia@cmu.edu
§Email: matt.mason@cs.cmu.edu

***Abstract*—We built an instrumented screwdriver stage to detect categories of failures not previously documented and to record their sensor information for future prediction. Our data collection process was arduous, relying on manual resets and data labeling, but the low incidence of failure in the operation required a large number of runs. Furthermore, the data collection process itself damaged the screws and affected the results. We intend to design another collection process with more automation to gather more and better data.**

I. Introduction

The study of automated robot screwdriving provides a useful sample application for exploring general manipulation ideas. Not only is the application relevant, since screwdriving operations make up a significant fraction of all assembly operations, but screwdriving itself is a mechanical operation simple enough to model straightforwardly but complicated enough to admit interesting behavior. Two helices in sliding contact demonstrate a variety of interactions and failure modes, and techniques used to understand their behavior can generalize to other, more sophisticated operations.

The study of screwdriving has historically focused on only a handful of failure modes. Screwdriving suffers from the same wedging and jamming failures that peg-in-hole assembly does, with the addition of cross-threading (see e.g. Nicolson and Fearing [3]). Research efforts to detect failures (e.g. [2]) have focused only on these few cases. However, when a system is actually deployed, numerous other failure modes occur. In order to identify these failures, we built an instrumented screwdriving stage and collected over 1800 screwdriving operations[1]. During the process, we encountered a variety of data collection challenges that are worthy of discussion.

II. Data collection

To collect the data, we built an instrumented screwdriving setup, equipped with a camera, six axis force/torque sensor, motor current and speed monitoring, and vacuum system for screw acquisition and holding (see Fig. 1). Screws were presented for acquisition in a shaker tray fixed in the workspace, and installed into a plate made with 100 screw inserts. Data was collected in batches of 100, with the screws removed and returned to the shaker tray by an operator after every batch.

Following the data collection, each run was manually examined (using the video and the data traces) to classify it into one of several emergent failure categories, and the run was also divided into its component stages. The failure type is straightforward to determine from the data traces; see Fig. 2 for samples. We extracted seven distinct failure modes and ten distinct intermediate stages, from which we computed a process model (Fig. 3).

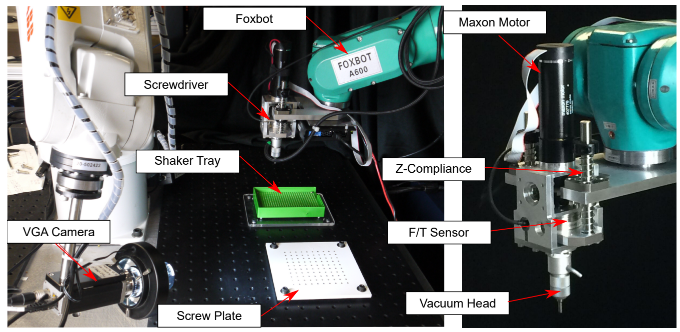

Fig. 1. The instrumented screwdriving station, drawn from Aronson et al. [1].

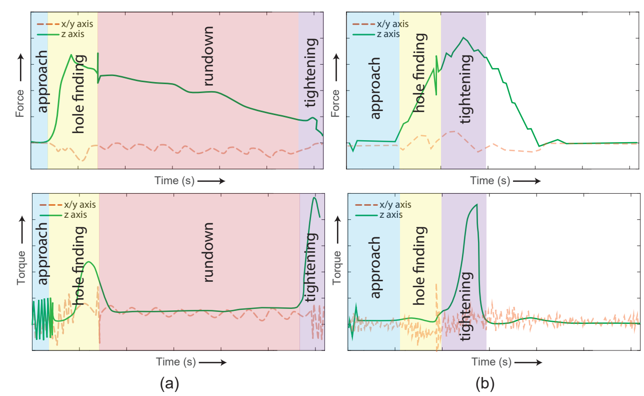

Fig. 2. Illustration of the force/torque traces for a success case and a cross-thread case, drawn from Aronson et al. [1].

III. Discussion

The overall success rate of the screwdriving operation was quite high, with about 85% overall success rate, and 10% of the remaining 15% failures came from failing to acquire a screw at the beginning of the operation. Therefore, the most interesting failure cases were confined to only about 5% of all

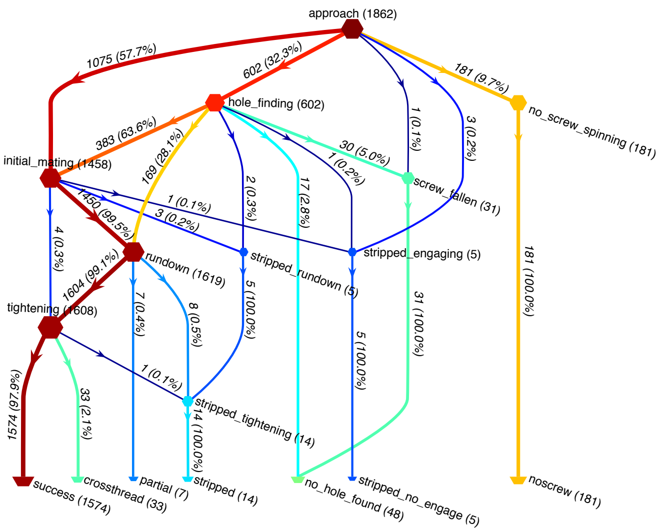

Fig. 3. A markov process model of the collected screwdriving data, drawn from Aronson et al. [1].

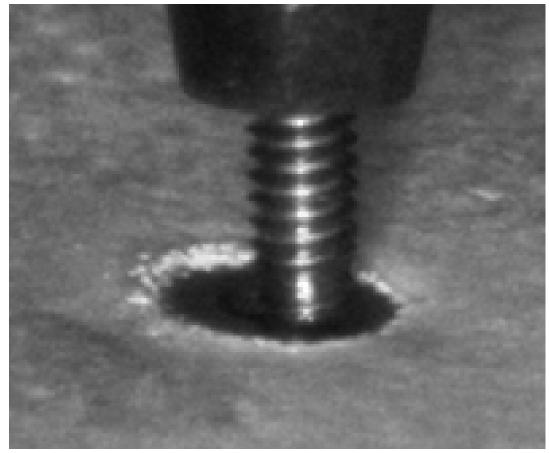

Fig. 4. A worn screw. Note that the final few threads above the hole are much less well defined than those further up the shaft.

collected operations. This “long tail” problem demonstrates the difficulty of exploratory data collection: discovering the rarer cases requires exponentially more data. Contributing to the difficulty was the fact that our first data collection process was highly manual. The screws were removed and reset manually, which required significant human intervention approximately every 45 minutes; the data was labeled manually, which took about 20 person-hours of work. While this manual process did manage to reveal more distinct failure categories than previously documented, nevertheless the number of incidences of each (the fewest occurred only five times) is not sufficient to perform full characterization and prediction. Thus, we are investigating additional automation of the process for our next data collection pass.

The collection method also influenced the data itself in unexpected ways. For example, repeated use of the same screw wore down the threads, potentially leading to additional failure modes caused by weakened threads and debris in the workspace (see Fig. 4 for an example). Industrial assembly setups rarely reuse screws, so the failure modes caused by this wear were not necessarily representative, either in type or quantity, of failures typical to the process. The specific details of our setup introduced these failures and enhanced their probability.

Furthermore, our lack of automation made these failures difficult to categorize. In particular, if we automated the screw removal and reset process, we would be able to track individual screws across multiple operations, and annotate each failure with how many times the screw had previously been used. Not only does increased collection automation enable more data to be taken more easily, it can even enable collection modes that are otherwise difficult to collect.

IV. Conclusions and Future Work

We are in the process of designing a new data collection experiment that will incorporate more automation and tracking to better isolate different error causes. The first collection process successfully identified a number of failure classes, but it intrinsically caused additional failures and failed to account for them. We can improve it to collect more and better data.

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