

A Dataset for Condition Monitoring of Screwdriver Bits based on a Piezoelectric Accelerometer for Machine Learning

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Abstract

To ensure high-precision industrial operations, monitoring assembly processes and tool health using machine learning has become critical. In automated screw assembly, screw bits are vulnerable to progressive wear and sudden damage, which can lead to workpiece defects and costly production downtime if not identified early. Conventional monitoring techniques often rely on torque or angle analysis; however, these typically provide post-process diagnostics rather than real-time insights.

This paper presents a high-resolution vibration dataset designed to advance research in real-time tool wear detection and process monitoring. The data was captured using a piezoelectric accelerometer mounted on an electric screwdriver, which recorded vibrations during both tightening and loosening cycles. To simulate industrial degradation, controlled wear was artificially induced on the bits across multiple incremental stages. The resulting dataset includes three independent experimental series, comprising varied screw hole manufacturing processes and randomized sequences to ensure model robustness and prevent overfitting. By providing well-annotated time-series data in MATLAB format, this resource enables the development of interpretable machine learning models that predict wear stages and recommend proactive tool replacement. Initial validation using time-frequency feature extraction and principal component analysis demonstrates clear signal separability, confirming the dataset's utility for both classification and regression-based condition monitoring.

Keywords: Assembly Process, Condition Monitoring, Interpretable Machine Learning, Process Monitoring, Screwdriver, Screw Bit, Wear Detection, Piezoelectric Accelerometer.

Introduction

Monitoring assembly processes and tool conditions using machine learning has become increasingly crucial to ensure the proper execution of industrial operations [1]. In screw assembly processes, which primarily involve tightening screws with electric screwdrivers, screw bits are subject to wear and damage over time [2]. Detecting their wear stage is essential to prevent workpiece damage and production delays or downtime. Previous studies have primarily focused on analyzing angle or torque signals to assess screwdriving performance [3]. While such approaches can detect bit damage, they only provide a diagnosis after the process is complete, making them inefficient for real-time decision-making [4].

This paper introduces a high-resolution vibration dataset collected from screwdriving processes to support research in tool wear detection and process monitoring. The dataset

enables the development of machine learning (ML) models that predict the wear stage of screw bits and recommend bit replacement before functional failure, thereby improving time efficiency and reducing resource use [5]. The dataset contains well-annotated measurements of both tightening and loosening processes. Controlled wear has been artificially induced on screw bits to represent incremental wear stages.

Experimental Setup

To collect the experimental data, a setup consisting of a screwing testbed, an electric screwdriver, and a data acquisition (DAQ) system is used (Fig. 1) [6]. A piezoelectric accelerometer is mounted non-destructively onto the screwdriver to capture high-frequency vibrations near the bit holder (Fig. 2). These vibration signals are essential to identifying the bit's condition and its level of wear [7]. To process the acquired data, a MATLAB-based ML toolbox developed at the Lab of

Measurement Technology (LMT) is used [8]. These models are employed to evaluate the dataset and confirm that early wear detection is indeed feasible with this approach.

The testbed comprises 16 screw holes, each manufactured through different processes, labeled A to D, to introduce signal variability to make the ML models more robust. Specifically, A and B are hand-cut and hand-formed threads, while C and D are machine-cut and machine-formed [9]. We excluded the four central holes because the shock absorber interferes with the screwing process (Fig. 3). The entire testbed slides along pins, which, combined with the shock absorber, help minimize counterforces during the tightening and loosening cycles [9].

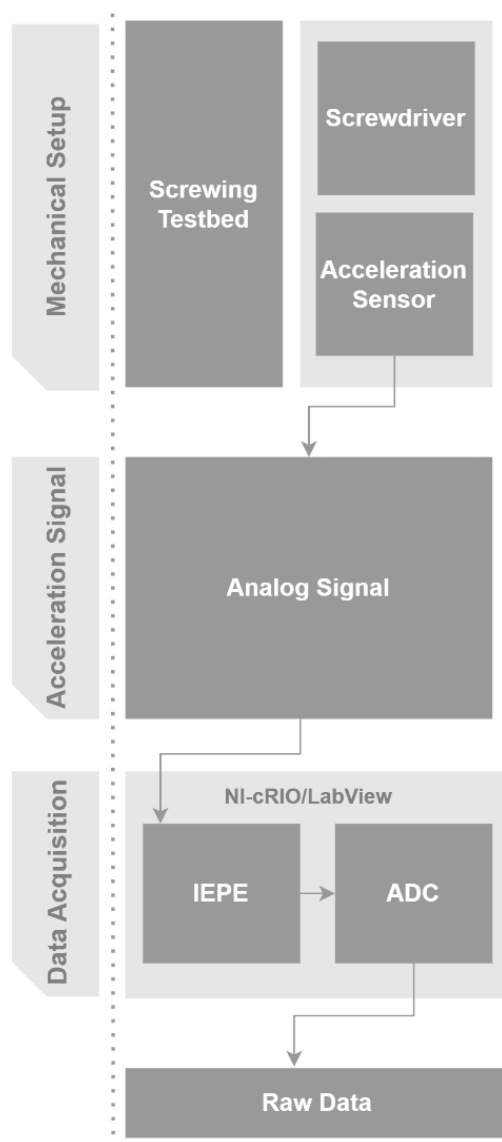


Fig. 1: Schematic representation of the data acquisition pipeline, illustrating the flow from analog signal generation at the sensor level to the digitized raw data formatted for signal processing.



Fig. 2: Handheld electric screwdriver with a piezoelectric accelerometer non-destructively mounted near the bit holder to capture process-related vibrations.

To execute the screwdriving operations, an electric angle- and torque-driven screwdriver (Rexroth, type DAH72736) was employed (Fig. 2). The device was operated in manual mode.

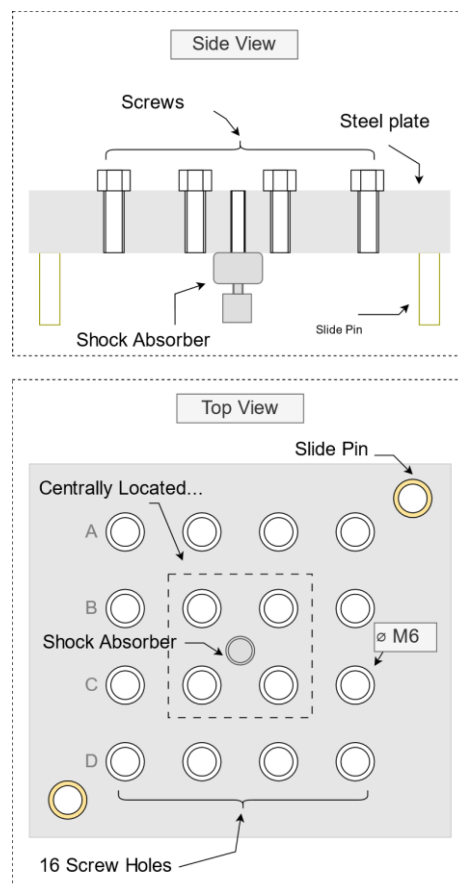


Fig. 3: Screwing testbed utilized for dataset generation. The four centrally located holes are excluded from the analysis due to signal interference from the shock absorber.

Vibrations are captured using a three-axis piezoelectric accelerometer (Dytran 3233A), as shown in Fig. 2. The sensor provides a sensitivity of 1000 mV/g and a frequency response range from 0.4 Hz to 6 kHz. For this study, only the z-axis data is analyzed, as the x- and y-axes are susceptible to coupling artifacts that could compromise signal integrity [10].

The screw bits investigated in this study feature a hexagonal socket geometry with dimensions of 25 mm in length and 5 mm in width, designed to interface with the M6 threaded holes of the testbed (Fig. 3). Three separate bits were evaluated. Initially, the baseline mass of each bit was recorded. Wear was then artificially induced through a controlled grinding process. Each wear stage corresponds to a uniform material reduction of approximately 10 mg (Table 1).

The generated acceleration signals were recorded using a data acquisition (DAQ) system equipped with an NI 9232 module (National Instruments) and an Integrated Electronics Piezo-Electric (IEPE) interface. This interface facilitates the low-noise transfer of high-dynamic signals by providing a constant current source to power the sensor [11]. Signal digitization is performed by an integrated analog-to-digital converter, which quantizes the signal at 24-bit resolution. The sampling rate was set to 20 kHz to provide comprehensive coverage of the high-frequency components present in the vibration data.

A cRIO-9040 control unit (National Instruments) collects the digitized data and stores it in the Technical Data Management Streaming (TDMS) format, a LabVIEW-native format optimized for large, continuous data streams. To ensure high transparency and reproducibility, each measurement is accompanied by detailed metadata specifying the testbed configuration, wear stage, and damage type (Fig. 4).

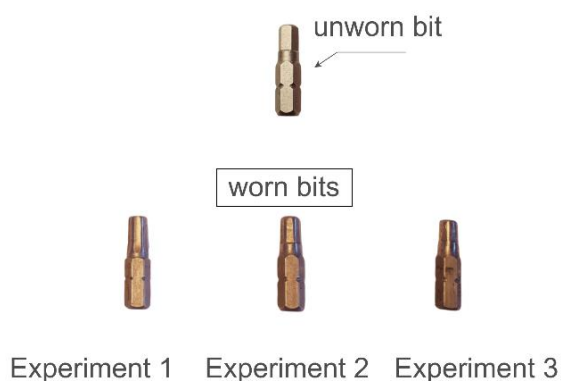


Fig. 4: Comparison between the unworn and worn bits

Table 3: Bits' weight and the corresponding wear stage.

Wear Stage	Bit 1 Weight (mg)	Bit 2 Weight (mg)	Bit 3 Weight (mg)
0	5568	5646	5728
1	5562	5635	5713
2	5556	5627	5699
3	5550	5610	5682
4	5544	5600	5667
5	5538	5580	5652
6	5527	-	-
7	5515	-	-

The presented dataset comprises time series data from three independent experiments conducted with three separate bits:

- Experiment 1 includes 8 wear stages (W_S).
- Experiment 2 and 3 each consist of 6 wear stages. The third experiment utilizes randomized screw hole sequences to enhance model robustness.

For each wear stage, two complete runs (R) are performed. Each run includes 24 individual screwing processes (S_P), divided into 12 tightening and 12 loosening operations across 12 screw holes (S_H), resulting in a final dataset of 960 time series:

$$12 S_H \times 2 S_P \times 2 R \times [8 + 6 + 6] W_S = 960$$

All time series data, along with the corresponding experimental profiles and labeling information, are provided in MATLAB .mat format.

Machine Learning Methods

This section details the methodologies applied to the acquired vibration data and outlines the general processing pipeline, including an exemplary workflow for wear detection (Fig. 5).

The raw acceleration data undergo automated segmentation into 2.5-second intervals to isolate individual tightening and loosening operations. Given the sampling frequency of 20 kHz, each interval comprises 50,000 samples. To enable real-time model responsiveness, these intervals are further subdivided into ten segments.

Due to the high-frequency nature of the acceleration signals, time-frequency analysis is employed for feature extraction. This approach ensures the interpretability of the features and the subsequent model [12]. The machine learning architecture incorporates a time-frequency feature extraction (TFEx) stage, illustrating the dataset's utility for interpretable machine learning [13].

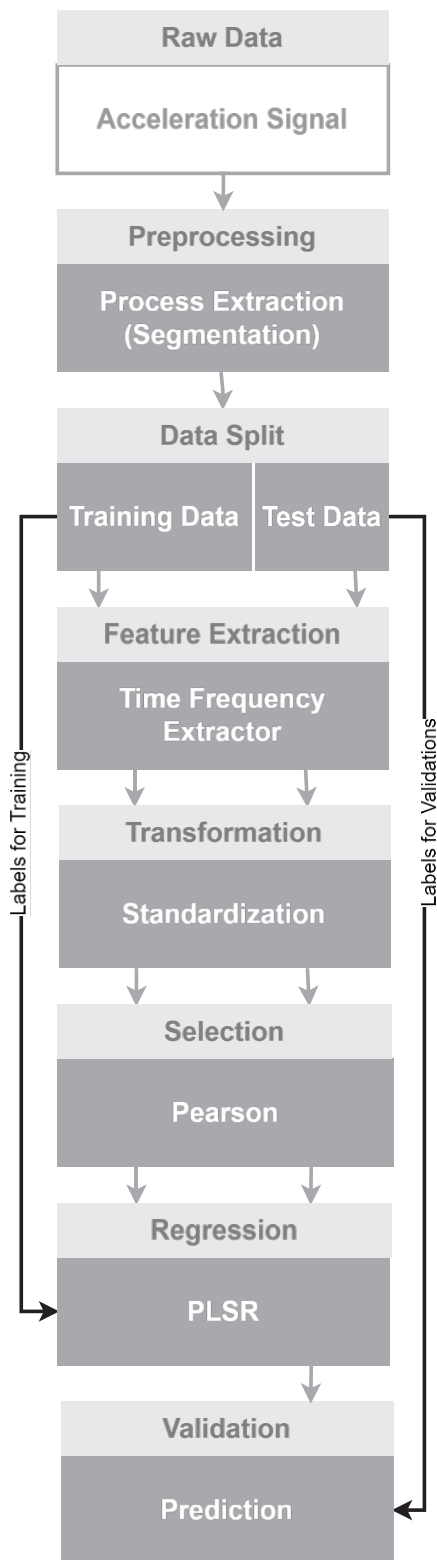


Fig. 5: Schematic of the ML architecture, illustrating the data processing pipeline from raw acceleration signals and segmentation to frequency-domain feature extraction and PLSR-based wear prediction.

Within the TFE module, the previously defined intervals are partitioned into 20 sub-intervals,

each of which is transformed into the frequency domain via the Fast Fourier Transform (FFT) [14]. Subsequently, each FFT-transformed signal is divided into 40 equal bins for final analysis [15].

Finally, statistical descriptors are calculated to construct the feature vector. These include kurtosis, linear slope, maximum and minimum values, the position of the maximum, root-mean-square (RMS), peak-to-RMS ratio, skewness, and variance.

To visually evaluate the quality of the extracted features, a Principal Component Analysis (PCA) was performed [16]. The resulting scores demonstrate clear cluster separability between the healthy state (indicated by blue markers) and the wear-affected states during the tightening process (Fig. 6, Fig. 7, and Fig. 8) [17]. Furthermore, a Pearson correlation-based selector was used to identify the most representative features [18]. To mitigate the risk of overfitting, this selector was constrained to the five most significant features.

Subsequently, a Partial Least Squares Regression (PLSR) model was trained against the wear labels to perform wear prediction, as is suitable for continuous prediction ranges as well as for noisy data [19]. The dataset architecture supports a robust validation strategy to mitigate systematic error. This strategy employs Leave-One-Group-Out Cross-Validation (LOGO-CV), where groups are defined by wear stages or screw hole types [20]. This workflow is referred to as the Feature Extraction, Selection, and Regression (FESR) stack [15].

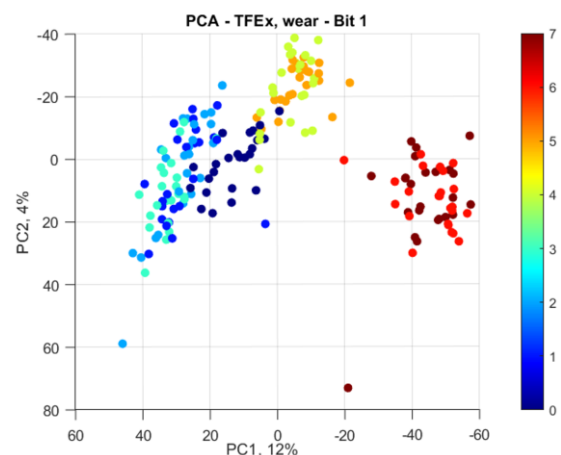


Fig. 6: PCA score plot of the time-frequency features (TFEx) extracted during the tightening process for Experiment 1. The projection onto the first two principal components (PC1 and PC2) illustrates the clear cluster separability according to the progressive wear stages of the bit.

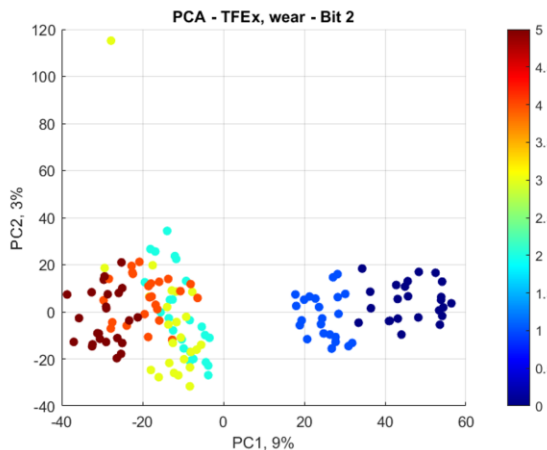


Fig. 7: PCA for Experiment 2. As for Experiment 1, the first two principal components capture the variance associated with bit degradation.

Results

Applying the processing pipeline (Fig. 5) yields a prediction error of 1.25 for the first experiment, 0.98 for the second, and 1.19 for the third. Since the model employs regression for prediction, the first and last wear stages of each experiment were excluded from the validation set, preventing the model from extrapolating beyond the defined training interval [21].

The validation results for the first experiment (stages 1 to 6) and the second experiment (stages 1 to 4) are presented in Figs. 8 and 9, respectively. These results demonstrate the feasibility of real-time wear stage monitoring. Consequently, a maintenance alert for bit replacement can be triggered as soon as wear stage 4 is detected.

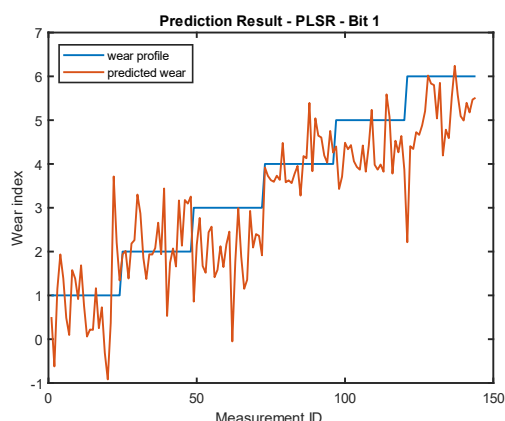


Fig. 8: Validation results for Experiment 1 using the PLSR model. The plot compares the predicted wear stages against the ground truth for stages 1 through 6.

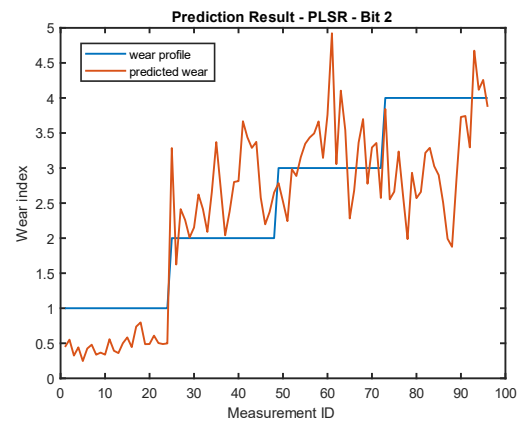


Fig. 9: Validation results for Experiment 2 using the PLSR-based regression. The plot compares the predicted wear stages against the ground truth for stages 1 through 4.

Conclusion

This paper presents a dataset for the condition monitoring of screwdriver bits utilized with a handheld electric screwdriver. Due to the high-frequency nature of the vibration signals generated during the assembly process, data acquisition was performed using a piezoelectric accelerometer. Furthermore, a machine learning model based on an FESR stack was developed and validated to demonstrate the feasibility of detecting tool wear. For the first experiment, the model achieved an average prediction error of 1.25 stages, representing the deviation from the ground truth. In the second experiment, the model reached a prediction error of 0.98 and remained consistent at 1.19 for the third.

While these results are promising, future work should focus on enhancing and validating model robustness through additional experimental trials. Furthermore, the model's transferability across different bit geometries and screwdriver types remains an area for further exploration.

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