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Interpretable Machine Learning Algorithm for Bit Damage Detection in a Screwing Process based on Accelerometers

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Introduction

Machine Learning (ML) and Deep Learning (DL) techniques were introduced in the industrial environment to improve processes and increase efficiency. Especially, in the production industry, assembly and screwing processes represent crucial processing steps [1].

Many mistakes during the assembly work and screwing process resulted in waste and decreased production line performance. Standard methods label the screwing process afterward as good or bad to inform further processing stations. This method does not consider the condition of the screwdriver and the related components. Those standard methods are based on internal torque and angle values to classify the screwing process,[2, 3] where the torque should reach a particular value for a specific angle and mostly focus on process labeling after a finished process [4]. However, many faults during the process are caused by damaged or destroyed screwdriver bits. The studies where the ML predictions are made after the process is finished do not avoid damage to the workpiece. Especially in the case of a full production line, where the screwing process represents one process (Fig. 1), are the focus of this study. To avoid damaged workpieces and to minimize downtown of the production line, the worker should be informed before the screwdriver is completely finished with the process.

Another challenge lies in the vast amount of parameters that can influence and disturb the screwing process, like used force, rotational speed, or geometry of the bit. On the other hand, several components could harm the process. This paper focuses on the bit of the screwdriver. All these different influences result in a more complex way of recording and handling data. This is furthermore reflected in the following data analysis and usage of Machine Learning (ML) models.

For this purpose, we will use models that are more robust against these influences, especially interpretable ML methods, consisting of Feature Extraction (FE), Feature Selection (FS), and Classification (C) algorithms, that gained attention in recent years [5]. The benefit of these algorithms is that they provide a physically interpretable representation of the

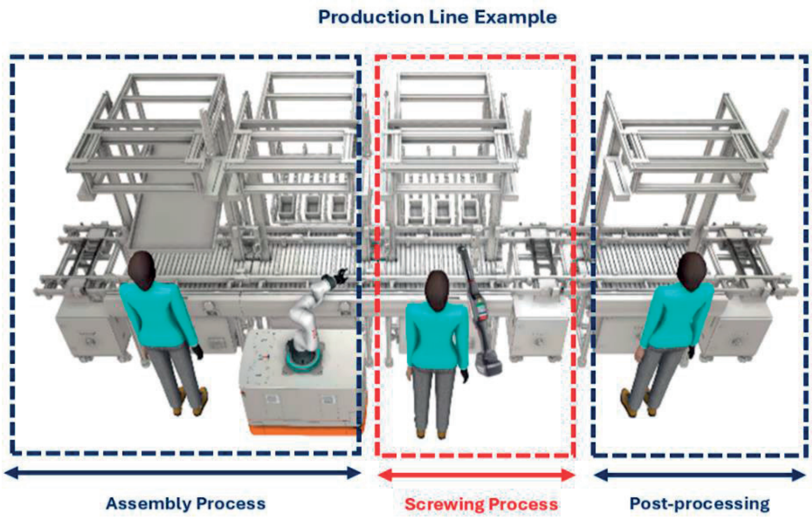

Figure 1 Example of a production line with multiple working stations including a screwdriver station

considered problem [6]. These physically interpretable representations allow the user to find and define robust and parameter-independent features to solve problems in a complex industrial environment. The goal of this paper is to detect damaged screwdriver bits during a screwing process to prevent failures in the downstream production process by increasing wear of the bit.

Testbed

In the field of data-driven methods like Machine Learning (ML) and Deep Learning (DL), the training and test data represent the most crucial and important influence on the ML method's quality [7]. For this purpose, a testbed with a total amount of 16 screwing holes and external sensors is designed, cf. Fig. 2. The testbed and the following experiment were designed to create a controllable environment where reliable data can be collected. To recognize and even prevent upcoming failures caused by a damaged or worn bit, an external accelerometer is placed on the upper plate to monitor the process in real time and make predictions already during the screwing process to indicate faults before the process is finished so that the user can replace the bit. The upper plate is made of hardened steel to prevent damage to the holes in the early stage of the data acquisition caused by the screws. An additional threaded hole mounts the sensor on the upper plate to measure the acceleration. This allows the accelerometer to measure the vibrations of the upper plate accurately. The additional force sensor is placed between the upper and lower plates of the testbed. The force sensor allows monitoring of the force that the worker uses to execute the screwing process. This allows *the* recording *of* consistent data and minimizing the influence of different force levels on damaged bits detection.

Measurement Setup

The measurement setup for the data acquisition consists of three different components, see Fig. 3. The first component is the mechanical setup, which includes the testbed and the screwdriver. The most important elements here are the accelerometer and the force sensor. The sensors connect the mechanical setup with the data acquisition system. The National Instrument NI 9232 signal acquisition module is an analog input module that allows data collection of a triaxial accelerometer. An additional NI 9245 digital input module is employed to collect force sensor data. Both modules are controlled over the cRIO-940, where the sample rate of both sensors is set and represents the second component of the data acquisition component. Due to limited knowledge of the frequencies of interest at the beginning of the experiment, the sample rate was intentionally set to a higher value of 20 kHz. This allows the selection and definition of the important frequencies in a further processing step.

On the other hand, 20 kHz displays an unnecessarily high sample rate for acquiring force data. The data are down-sampled in a further processing step to avoid redundant information. After the cRIO-940 collects the data, the internal Laboratory Virtual Instrumentation Engineering Workbench (LabView) program saves the continuously collected data into a TDMS file—the last component of the data processing, which is executed in MATLAB. Different algorithms tested against each other are ML algorithms implemented in the LMT-ML Toolbox and can be tested automatically [8].

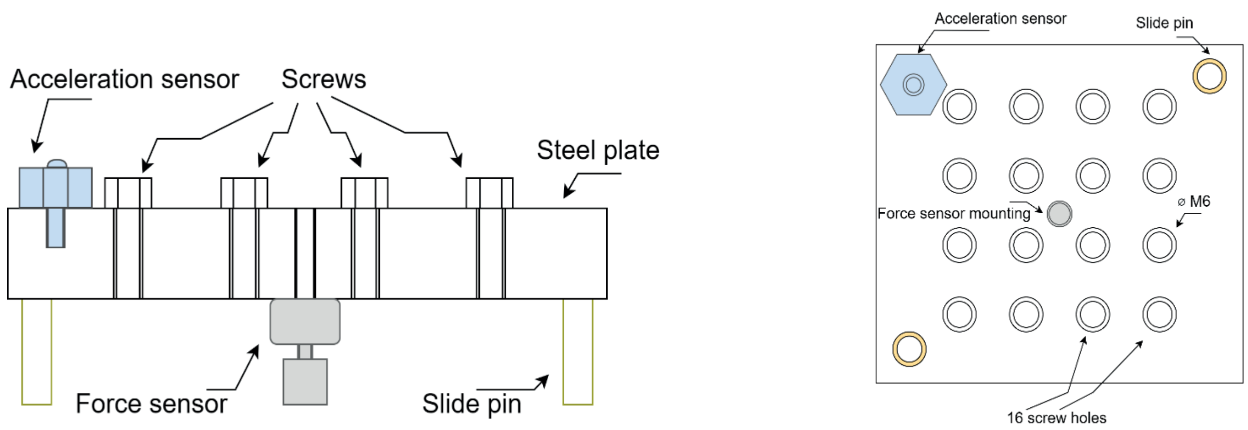

Figure 2 The designed testbed for the acquisition of screwing process data

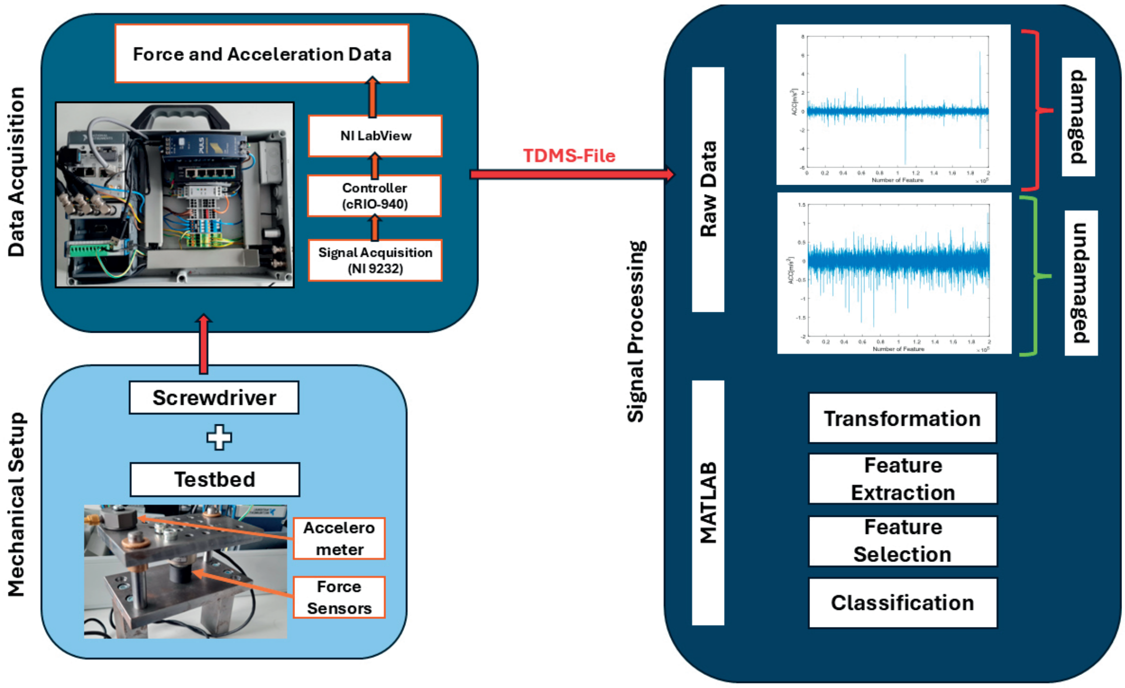

Figure 3 The different components for the acquisition system

Machine Learning algorithms

Besides acquiring an appropriate testing data set, this paper presents a feature extraction, selection, and classification (FESC) algorithm that classifies the screwdriver's wear. The algorithm allows the user to interpret the data in each processing step and classify processes in real-time. The best algorithm validated with the LMT-ML Toolbox [8] consists of four signal-processing steps, explained in the next section. The toolbox comprises several algorithms for each stage and selects the best combination based on the highest cross-validation accuracy.

Transformation

This signal-processing step transfers the collected raw data into a different domain to provide a more detailed representation of the original data. The frequency domain often represents a better foundation for the analysis of data collected with an accelerometer. For this purpose, the collected raw data were transformed by Fast Fourier Transformation (FFT) [9] before the actual FESC algorithms are applied.

Feature Extraction (FE)

The FE algorithms use physically interpretable extracted features to reduce the data dimension by representing it. Hence, the FE algorithm represents

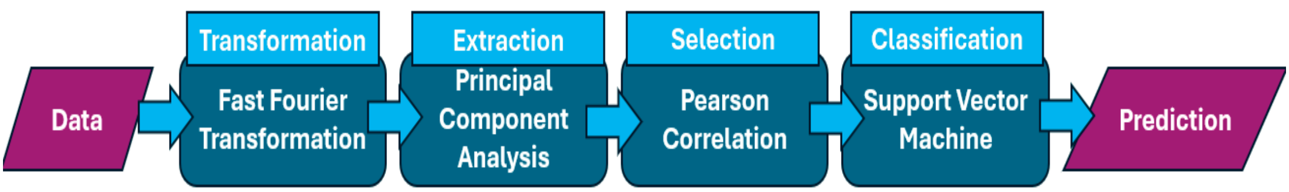

Figure 4 Designed data workflow, including transformation, extraction, selection and classification algorithms

the input data in different ways. To represent the recorded data with a lower dimension but with the most available information value, there is a tradeoff between approximation error and the low number of features. The algorithm that showed the best results in this use case is the Principal Component Analysis (PCA) Extractor [10]. The PCA reduces the input dataset's dimensionality by applying an orthonormal coordinate system transformation, keeping only the first dimensions representing the highest variance or information content. The explained variance decreases with the number of the Principal Component (PC).

Feature Selection (FS)

After extracting significant features, the FS narrows the extracted features to those with the most information value. This selection avoids overfitting during the training process. The FS learns the most significant features calculated by previously executed FE in the training process. The Pearson correlation [11] describes the linear correlation between the extracted features and the target. Pearson was identified as the most effective FS algorithm for the screwdriver's use case.

Classification

The last element of the FESC pipeline consists of the classifier algorithm, which calculates the output of the FESC. This workflow element is a supervised and trainable step. Classifiers intend to map the given input to the desired discrete output with a minimal error rate. As an appropriated classifier, a Support Vector Machine [12] was trained on the selected features to classify whether the screwdriver bit is damaged. The SVM defines hyperplanes, which separate the different classes. The SVM in this use case works as a linear classifier.

Validation

The results are validated using a threefold stratified cross-validation. The dataset is partitioned into three subsets of equal size, and the class distribution within the subsets is nearly equal. For each fold, the model is trained on the remaining two subsets of the dataset. The resulting model is then applied to the test fold, and the overall accuracy is calculated based on the test prediction for all three folds.

Data

The data collected by the measurement system are briefly introduced in this section. The data acquisition of one screwing process with a constant rotational speed for the whole data set was monitored with a force sensor placed between the two plates. Fig.5 shows the force for the duration of one screwing process, which has a slight decrease during the process. Because the process is executed manually, it is not possible to keep the force perfectly constant for the whole screwing process. However, the recording of the force data allows a following analysis regarding the force used during the screwing process.

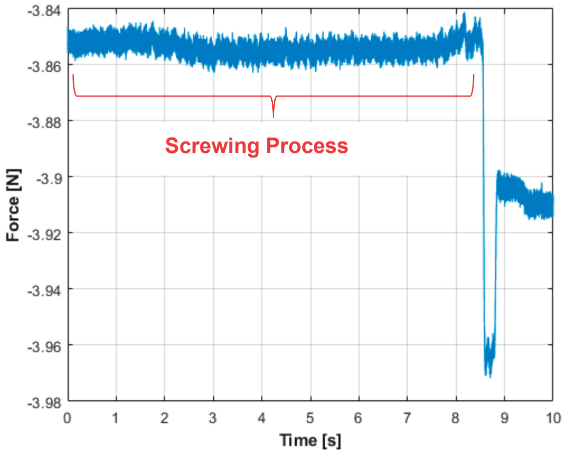

Figure 5 Example the force data of a screwing process

Fig. 6 shows the data of the accelerometer in the time domain. The difference between the damaged and undamaged bit is visible due to peaks occurring with a higher amplitude. But especially for the accelerometer, the time domain does not represent a robust problem representation. Due to external vibrations, which could result in peaks, focusing on the time domain signal could lead to false classification.

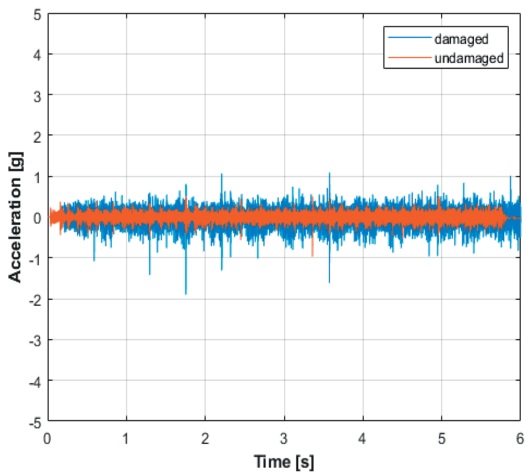

Figure 6 Example of the acceleration data during a screwing process

To avoid those false classifications, the signal data of the accelerometer is transformed into the frequency domain with the FFT. Fig. 7 shows the spectrum of the acceleration data in the damaged and undamaged cases. The sample rate of 20 kHz sets the limitation of the maximum visible frequency. This means that frequencies over 10 kHz are not calculated with the selected FFT. In the undamaged case, low frequencies display the dominant part of the spectrum. Besides the increased amplitudes, damage to the bit-high frequencies occurs in the spectrum. The comparison in the frequency domain results in a visible and robust distinction between damaged and undamaged bits.

Results

The extraction of the features is executed with a PCA Extraction. The PCA extraction is applied on the spectrum of the accelerometer. Fig. 8 shows the plot of the first two Principal Components (PC). The percentage values on the axis of the plot name the percentage of the variance, which is described through the corresponding PC. The plot demonstrates the well separatable classes after the PCA extractor. Besides a small number of overlapping points two clearly separated clusters can be seen. Due to the well separability, an SVM is suitable as a linear classifier. In Fig. 9, the training targets, consisting of damaged (= 1) and undamaged (= 2) labels, are plotted over the 3-fold Cross-Validation prediction. The algorithm reaches an accuracy of 98.1 %.

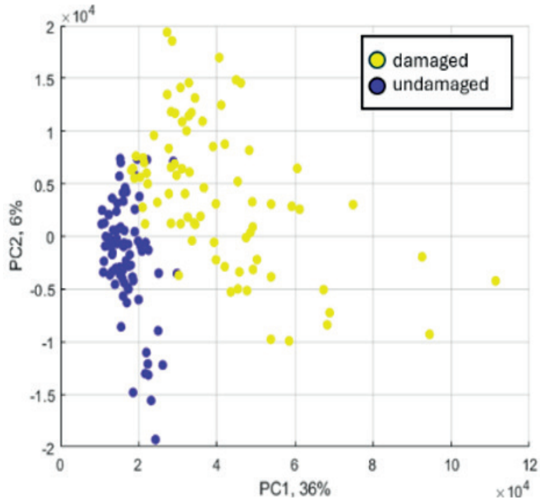

Figure 8 Principal component analysis of the Fast Fourier transformed data

Discussion

This paper successfully developed a method for the classification of damaged bits. This method allows detection of damaged bits during the screwing process. Nevertheless, only one damaged and one undamaged bit were investigated in this work. Furthermore, the recorded data set only consists of 160 total time series, where half contains damaged and the other half undamaged time series. The force sensor was used to record consistent data with a constant force. Besides the investigated damage in this study that focuses on the damaged bits, several different damages can occur during a screwing process. Furthermore, the damage to the bit, the screws, or the screwing hole may involve wear, which also affects the accelerometer data.

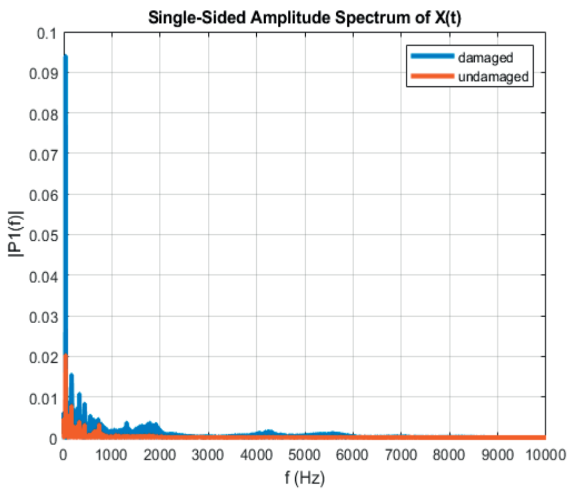

Figure 7 Spectrum of the damaged and undamaged screwing process

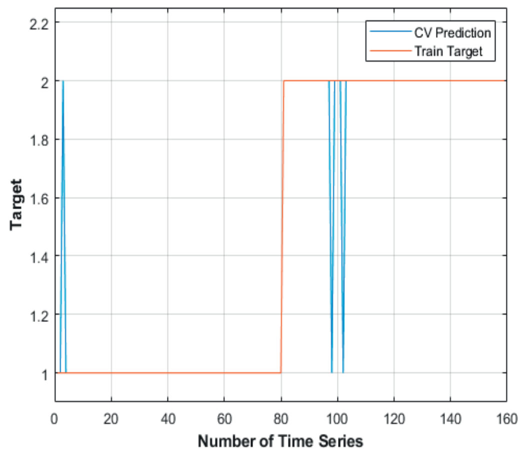

Figure 9 Cross validation classification result of the trained algorithm

Therefore, significantly more experiments need to be carried out to enable a reliable classification.

Conclusion and Outlook

This paper presented an algorithm to classify damaged and undamaged bits in a screwing process. The classification is based on an interpretable ML stack, which explains different characteristics at various signal-processing stages. The method transforms the time domain acceleration data into the frequency domain and predicts based on the occurring frequencies. This approach helps identify changes in the signal and leads to a robust design. In addition to the algorithm, the paper outlines the design of an appropriate testbed to acquire data for screwdrivers. With the testbed, it is possible to acquire more data, focusing on parameters such as damage to different components, which should be included in future investigations. Currently, the algorithm detects whether or not the bit is damaged. Future research should explore the possibility of predicting bit wear, transitioning the problem from classification to regression.

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