Dataset for AI-assisted detection of the wear level of a cutting tool on a CNC mill

Marcel Jongmanns[1] (marcel.jongmanns@ipms.fraunhofer.de), Philipp Städter[2], Tenia Meisel[1]

[1]Fraunhofer IPMS, Dresden, Germany

[2]Brandenburgische Technische Universität Cottbus-Senftenberg, Cottbus, Germany

Licensing

Abstract

A METROM CNC mill was equipped with a microphone and an accelerometer to determine whether the used milling tool was in a good state or blunt. The measurement data was collected over several measurement series. The used tool was replaced at the beginning of each series with a new, similar tool. The working material was always steel. Machine parameters such as feed rate and rotational speed of the tool has been varied between different series. The machine was operated over a defined time frame while data was collected. After that, the machine was stopped, and the operator classified the quality of cut. The quality is directly related to the condition of the tool. The higher the wear, the worse the quality. Using this approach, we build a dataset consisting of different measurement series to show the degradation of a CNC cutter using vibration and acoustic measurements.

Data origin

The data is part of the iCampus – Fortune project funded by the Federal Ministry of Education and Research of Germany (BMBF), grant number 16ES1128K. The motivation of the project was to test the possibilities to design a system including sensors, data acquisition, and machine learning data evaluation for retrofitted condition monitoring of machines[1].

Measurement setup

A METROM CNC mill was equipped with an accelerometer and microphone (Figure 1). The CNC mill is fully encased and uses a pentapod geometry to move the spindle with the tool. The accelerometer is an Analog ADXL1005, and the wideband MEMS microphone is a Knowles SPU0410LR5H. The data was sampled by a modified version of the Fraunhofer IPMS CMUT evaluation kit[2]. The sampling rate of the analog inputs was set to 1.953.125Hz.

[1] Assafo, Lautsch, Suawa, et al., The For-Tune Toolbox: Building Solutions for Condition based and Predictive Maintenance Focusing on Retro Fitting, 2023, MST Kongress

[2] https://www.ipms.fraunhofer.de/en/applications/Customer-Evaluation-Kits/CMUT-Evaluation-Kit.html

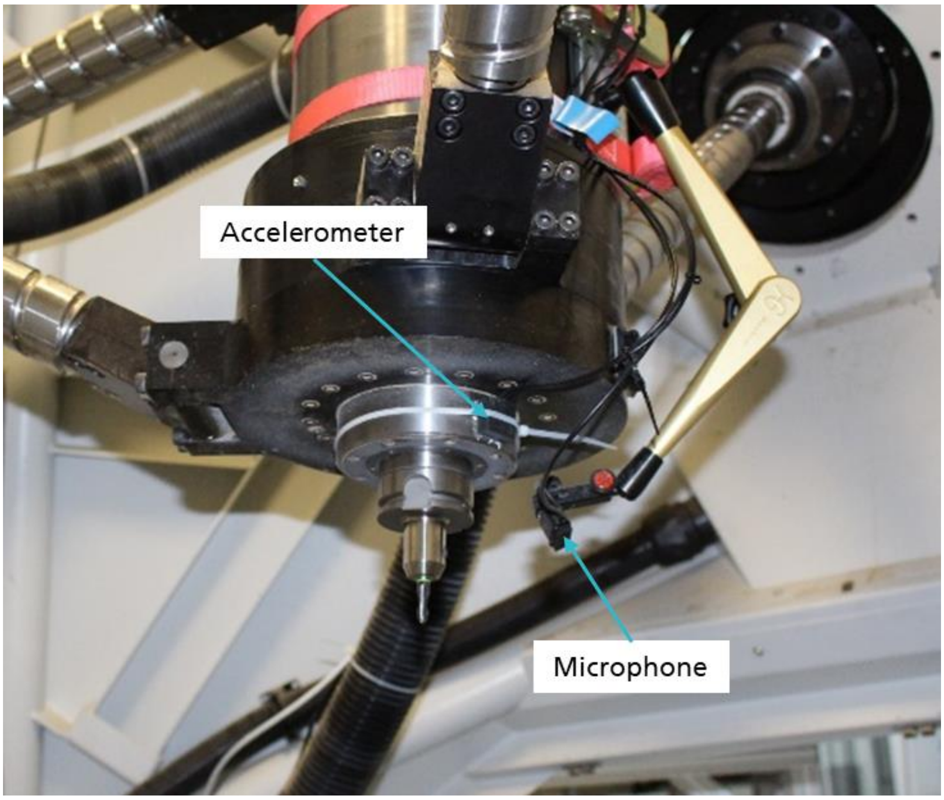

Figure 1: The accelerometer is glued and strapped to a stationary part of the spindle. The microphone is positioned towards the tool by a beam.

The accelerometer was mounted at a stationary part of the spindle to measure vibrations caused by the tool. It was fixed using adhesives as well as a cable tie. The microphone was mounted using a beam to be near the tool. It was aimed towards the tool and protected by a fabric against loose chips emitted by the tool. While the flying chips could not damage the sensors, they could very well interfere with the measured sounds. During the operation of the machine, no lubricant or additional cooling was used.

Measurement process

All measurements have been performed with the same type of tool. The tool has a diameter of 8mm and 2 cutting edges. It was replaced with a new, similar one at the start of each measurement series. The working material was in all presented cases tool steel. The CNC mill is moving back and forth over the length of the whole material. Thus, one lane was milled using synchronous milling and the next one with upcut milling. After each lane, the tool was outside the material spinning in air. These events are important to consider in the evaluation but are not labeled in the data. As a general guideline, the amplitudes of the signals are lower when the tool is spinning in air than when it is in contact with the material.

The machine parameters like feed rate and rotational speed of the tool have been varied to wear the tool down at different rates. The exact machine parameters can be found in the accompanying Excel table. Note, that there are different sheets for *steel* and 4 parameter variations.

Each step of the measurement has a variable length. After each step the quality of the cut was evaluated. This can be done based on the markings on the material and the produced chips during the milling process (Figure 2). Usually, when the tool is sharp, the cut shows a regular pattern caused by the cutting edges. When the tool is blunt, this pattern disappears. Using these features, the cut edge of the material can be evaluated as well. The more prevalent the burr on the cuts, the blunter the tool is. The chips roll up and keep the color of the material when the tool is sharp and become discolored and do not roll up when the tool becomes blunt. These indicators were used to label the health state of the tool for each step.

For some tools the cutting edge has been characterized using microscopy as shown in Figure 3.

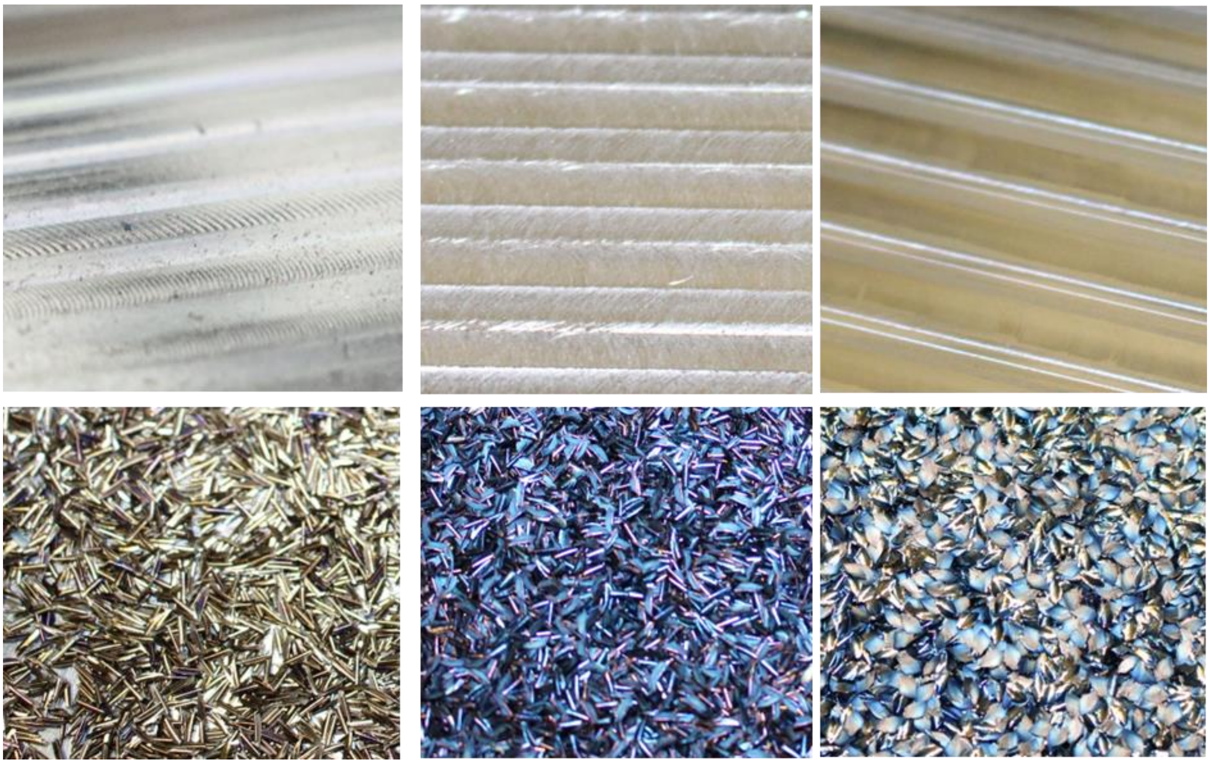

Figure 2: Different quality levels of cuts on the material (top) and of chips (bottom). Left: Good cut with rolled chips. Middle: Degraded cut with burned, but still rolled, chips. Right: Bad cut with non-rolled chips.

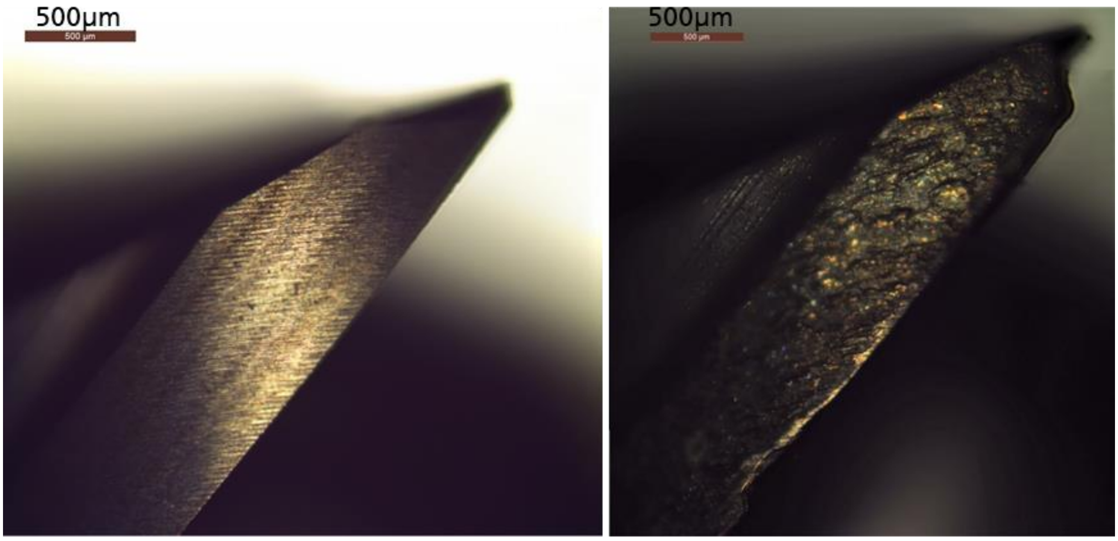

Figure 3: Microscope image of a new, sharp tool (left) and worn-down tool (right).

Data format

The raw measurement data is presented as HDF5 file. HDF5 is an open data format which can be loaded in many programming languages, e.g. Python (Figure 4).

The data is divided into 5 datasets: *steel* and 4 parameter variations. The *steel* dataset includes 5 measurement series with a new, sharp tool for each series. Each file is divided into several groups labeled as given in the Excel table. Each group contains the microphone data *microphone*, and the accelerometer data *vibration*. Each of these is a 2-dimensional array of variable length in the first dimension, depending on the number of measurements, i.e. length of the measurement, and a fixed length in the second dimension of 16381, which is the number of samples in this time series data. The data is sampled at 1.953.125Hz. It is advised to apply a low-pass filter to the data, e.g. 100kHz to the microphone and 40kHz to the vibration data.

```
import numpy as np
import h5py

# Open file
f = h5py.File('steel.hdf5', 'r')

# Show groups in file -> Labels correspond to the numbers in the Excel table
f.keys()

# Show data in group '10' -> Always 'microphone' and 'vibration'
f['10'].keys()

# Get microphone data from series 10 as numpy array
mic_data = np.array(f['10']['microphone'])

# Get the size of the array
# Dimension 1 depends on the length of the measurement
# Dimension 2 is always 16381, the number of samples per time series
np.shape(mic_data)

# Close file
f.close()
```

Figure 4: Example of opening the HDF5 file in Python using h5py and numpy libraries.

For the *steel* and *parameter 2* datasets, there are also images of the tools, markings on the material and chips at different points in time during the wear down process.

Also note, that in the *steel* dataset not all labels are used. E.g. there is no group '30'. It is included in the HDF5 file, but the data is simply *0*. You can refer to the Excel table for this as well.

Previous work on the data

Assafo, Maryam; Städter, J. Philipp; Meisel, Tenia; Langendörfer, Peter (2023): On the Stability and Homogeneous Ensemble of Feature Selection for Predictive Maintenance: A Classification Application for Tool Condition Monitoring in Milling, Sensors, vol. 23, no. 9. https://doi.org/10.3390/s23094461

Suawa, Priscile; Halbinger, Anja; Jongmanns, Marcel; Reichenbach, Marc (2023): Noise-Robust Machine Learning Models for Predictive Maintenance Applications. IEEE Sensors Journal. https://doi.org/10.1109/JSEN.2023.3273458