Pre-processing for vibration signals features extraction and selection in real time investigating of CNC tool wear

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Abstract. This research attempts to investigate CNC milling tool wear based on machining vibration signals. Vibration data acquisition uses devices from NI DAQ USB-6008 and the analog accelerometer sensors, MMA 7361. Vibration feature extraction is done based on statistical analysis of time domain vibration signal and order domain vibration analysis. Feature selection using filter approach with the Linear Discriminant Classifier, successfully selected 10 main features. Whereas the multi-layer perceptron is used as the final classifier. When implemented on the CNC milling process, this system successfully detects tool wear with an accuracy of 96.4%. Error detection that still occurred consisted of 4.4% missed alarm and 2.8% False alarm.

1. Preliminary studies
The phenomenon of vibration and its correlation with the operating conditions of a machine have been extensively studied[1][2][3]. Vibration analysis is widely used in various machinery. Zhonghai, et.al[4] diagnosed hydraulic pump failure based on pump vibrations. Xingjian, et.al[5] predict the remaining life of an axial pump based on its vibration. Phadtare, et.al.[6] improved the reliability of rotating machinery using vibration analysis. Hassan[7] diagnosed the failure of the belt-pulley system also using vibration analysis. Even vibration analysis is also useful for detection of pump cavitation[8][9]. This includes investigating tool wear using vibration analysis[10][11][12][13], even to predicting the remaining tool life[14].

2. Prior arts
The phenomena commonly investigated in tool wear detection are surface finish[12], vibrations[15], acoustic emission[11][16], cutting forces[17][18], temperature[12], power consumption[19][20] and noise[21]. These quantities are affected by machining conditions and tooling conditions[12]. And the sensors used for tool wear detection are accelerometers[15], acoustic emission sensors[16], dynamometers[17], termometer[12], microphone[21] and power analyzer. The signal obtained from this sensors is still contained noise. This noise needs to be reduced and even eliminated so that it does not interfere with the next signal processing[22][23]. Various pre-processing techniques and feature extraction were developed to obtain meaningful information from signals that contain noise, including...
cepstrum analysis[24], spectral amplitude modulation[25], spectral substraction[26], wavelet transform[27] and wavelet packet decomposition[28] and order analysis[29].

3. Problem statements and objective of experiments
How to detect CNC tool wear with affordable inexpensive sensors? What vibration signal features are correlated with CNC tool wear? How does the performance of the classifier system detect tool wear? This study aims to investigate CNC tool wear by only using analog accelerometer sensors to record CNC milling vibrations and phototransistor for proximity measure spindle speed. Seeks features of spectrum order frequency domain and feature of time domain vibration that can be used as input classifier. Build and train a Multi Layer Perceptron as a classifier to detect tool wear.

4. Procedure and setup of experiment
The CNC milling machine used in this research is the Hercus V300 with Nachi HSS 12mm diameter four flutes end mill. Machining parameters of up milling with 0.2mm depth of cut on mild steel and 6mm cutting width. Spindle speed variations are 550rpm, 650rpm, 750rpm and feed rate variations of 0.02mm/tooth, 0.05mm/tooth, 0.08mm/tooth.

The sensor used is MEMS accelerometer MMA7361 to record vibrations in three axes and SFH-300 phototransistor. Data acquisition systems used are NI DAQ USB-6008 and Matlab script. The measurements through DAQ are calibrated by comparison through the oscilloscope GDS-1102A-U. Signal pre-processing is performed to clean the signal from the noise power grid and the mechanical natural frequency of the CNC milling machine. This natural frequency was analyzed by impact test experiment on Hercus CNC machines. Signal feature extraction is performed by statistical analysis of time domain vibration and order domain vibration analysis. Feature selection is performed using a filter approach using the Linear Discriminant (LD) Classifier. And the final classifier used in this research is the Multi Layer Perceptron with the gradient decent training method.

5. Results and discussion
5.1. Instrument calibration
Measurements through DAQ were conduct at 2500 Hz sampling rate with sampling time of 250 ms, resulting in 625 measurement datapoints (Figure). Measurements through oscilloscope were conduct at 10 kHz sampling rate with the equal sampling time of 250 ms, resulting in 2500 measurement datapoints (Figure). Resampling of the oscilloscope measurements with a factor of 2500/10000 is performed to obtain an equivalent number of datapoints. Paired T-tests were conduct DAQ datapoints samples and datapoints resample of oscilloscope measurements. Statistical test results proved no significant difference in the DAQ measurements with the oscilloscope measurements.
Figure 2. (a) 625 sampling of DAQ instrument measurement. (b) 2500 sampling of oscilloscope measurement. (c) 625 resampling of oscilloscope measurement. (d) the different of DAQ measurement and oscilloscope measurement.

5.2. Feature extraction
The results of the vibration signal recording give 1024 datapoints for each sample. There are 1800 vibration samples from CNC machining vibration using normal end mill tool and worn end mill tool. The vibration signal feature in the time domain is extracted from the statistical analysis of the datapoints distribution including standard deviations, skewness, kurtosis, and range of data. To get the frequency content of the vibration signal, a Fourier transformation is performed. Then the frequency spectrum is normalized to the spindle rotation so that the order spectrum is obtained from the first order of frequency to the 90th order of frequency. The features of each sample are arranged into row matrices equation 1.

\[
\text{FeatureAndLabel}_i = (\text{stdx}_i \quad \text{skwx}_i \quad \text{kurt}_x \quad \text{rangex}_i \quad \text{stdy}_i \quad \text{skwey}_i \quad \text{kurty}_i \quad \text{rangey}_i \ldots \quad \text{stdz}_i \quad \text{skwz}_i \quad \text{kurtz}_i \quad \text{rangez}_i \quad X_{1\text{th}} \quad X_{2\text{th}} \ldots \quad X_{90\text{th}} \ldots \quad Y_{1\text{th}} \quad Y_{2\text{th}} \ldots \quad Y_{90\text{th}} \quad Z_{1\text{th}} \quad Z_{2\text{th}} \ldots \quad Z_{90\text{th}} \quad \text{Label}_i ) ...eq(1)
\]

5.3. Feature selection
Feature normalization is performed to build zero mean and unity variance features before performing feature selection. Feature selection is done by correlation analysis, calculating the correlation coefficient of each feature to the conditions of tool wear and sorting from the largest to the smallest coefficient of correlation. Selection of features is done using the LD classifier with the forward selection method.
Based on this analysis, the top 10 features were selected, stdz, rangey, X2th, stdx, rangex, stdy, rangez, Y13th, Z13th, Y2th.

Figure 3. The performance of forward selection Linear Discriminant Classifier.

5.4. Multi layer perceptron classifier

Multi-layer perceptron (MLP) with a single hidden layer consists of 2 neurons and tansig - tansig activation function trained using the gradient descent with momentum (GDM) algorithm with a momentum coefficient of 0.9 and a learning rate of 0.1. Three iterations of MLP learning were performed using the GDM algorithm, followed by the classification test using test datasets and validation datasets (table). It appears that testing accuracy of the trained MLP is in accordance with Mean Squared Error (MSE) of the trained MLP based on testing datasets. Mean Squared Error of the trained MLP based on testing data and MSE of the trained MLP based on training data are not always the same, this is due to the random separation of training datasets and testing datasets. Highest testing accuracy, iteration 2 in this test group is not in accordance with high validation accuracy. The lowest validation accuracy actually occurs in iteration 2 which incidentally has the lowest MSE training in this testing group.

Table 1. Summary of the classifier performance during training, test and validation phase.

| MLP GDM Iteration | MSE      | Gradient   | Missed | False Alarm | Accuracy | Missed | False Alarm | Accuracy |
|-------------------|----------|------------|--------|-------------|----------|--------|-------------|----------|
| 1st               | 0.0312   | 3.19E-04   | 5.2%   | 7.8%        | 93.3%    | 5.0%   | 2.8%        | 96.1%    |
| 2nd               | 0.0297   | 0.000855   | 3.1%   | 3.6%        | 96.7%    | 8.3%   | 3.9%        | 93.9%    |
| 3rd               | 0.0336   | 0.000319   | 4.6%   | 4.3%        | 95.6%    | 4.4%   | 2.8%        | 96.4%    |
| Best              | 0.0297   | 0.000319   | 3.1%   | 3.6%        | 96.7%    | 4.4%   | 2.8%        | 96.4%    |
| Mean              | 0.0315   | 0.000498   | 4.3%   | 5.2%        | 95.2%    | 5.9%   | 3.2%        | 95.5%    |
| worst             | 0.0336   | 0.000855   | 5.2%   | 7.8%        | 93.3%    | 8.3%   | 3.9%        | 93.9%    |

6. Conclusion and future work

This research succeeded in developing the detection system to investigate the CNC mill tool wear during the machining process. The tool wear detection achieves the best accuracy of 96.4% when implemented in the CNC milling machining process. The detection error that occurred consisted of Missed alarm of 4.4% and False alarm of 2.8%. These results did not much differ from the accuracy of detection systems based on the training datasets.
Further research that can be performed is to attempt other methods for feature selection, or other method for reduction of feature dimensions, try the other classifier methods and compare the results of this research, or optimize the parameters of artificial neural network training in this study.

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