On-line Tool Wear Detection on DCMT070204 Carbide Tool Tip Based on Noise Cutting Audio Signal using Artificial Neural Network

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Abstract. This study develops an on-line detection system to predict the wear of DCMT070204 tool tip during the cutting process of the workpiece. The machine used in this research is CNC ProTurn 9000 to cut ST42 steel cylinder. The audio signal has been captured using the microphone placed in the tool post and recorded in Matlab. The signal is recorded at the sampling rate of 44.1 kHz, and the sampling size of 1024. The recorded signal is 110 data derived from the audio signal while cutting using a normal chisel and a worn chisel. And then perform signal feature extraction in the frequency domain using Fast Fourier Transform. Feature selection is done based on correlation analysis. And tool wear classification was performed using artificial neural networks with 33 input features selected. This artificial neural network is trained with back propagation method. Classification performance testing yields an accuracy of 74%.

1. Introduction

The cnc machine is capable of operating without operator supervision during machining. But in machining in cnc machine there is a risk of failure. Among the risk of failure is the damage tool and tool wear[1][2][3]. Tool breakage can occur suddenly, while the tool wear occurs gradually[4][5][6]. As a result of the wear tool is the decline in the quality of CNC machine work [7][8]. In order to maintain the quality of CNC machining, we need a system capable to monitor tool wear when machining progresses. This study aims to build on-line system detection tool wear.

2. Related work

Research on the detection of wear and tool breakage has been done by many researchers, general research on tool wear is done using a tool that wear out naturally[5][9] as well as a tool that wear out artificially [10]. Research on tool wear using the tool that wear out naturally generally done in two ways: to observe the gradual wear [11][10] and observed the classification tool wear with normal tool [12][13][14]. And the machine that is often researched is the lathe [5][15][16] or the milling machine [17][18]. This study observes and classifies normal and worn-out tools on CNC lathes.

Generally speaking, the process of wear and tear detection tool through the stages of capturing the observed physical signals, signal feature extraction that characterizes the tool's wear, selection and reduction of signal features for the classification process, and the latter is the classification of tool wear.
conditions based on the selected signal feature [19]. Various methods using various sensors are done to capture the physical signal from the CNC machine. To capture the vibration phenomena generated from machining, one uses an accelerometer [2][5] to capture the vibration of a machine or to use a microphone to capture audio noise. Methods performed by other studies capture acoustic emission signals using acoustic emission sensors [20][21]. There is also a tool wear detection study based on the measurement of energy consumption in spindle motor and motor feeder[1]. The study by Jacob[22] detects the wear of the tool based on the cutting force measured by the dynamometer. The study in this paper detects the tool wear on the lathe machine based on the noise of the cutting sound.

Feature extraction in this study was performed on frequency domain with fast fourier transformation. Other studies perform feature extraction in various ways, including wavelet decomposition, domain order transformation, energy spectrum, chirp detection. Selection of features in related research is done by two approaches, namely filter approach or wrapping approach. Selection of features is done by method of regression analysis, linear discriminant analysis, principal component analysis, KNN, decision tree, genetic algorithm. And many classification systems use statistical pattern recognition, genetic algorithms, artificial neural networks.

3. Overview of system and experimental setup

The on-line tool wear detection system consists of hardware and software. The hardware of the experimental detection and setup system presented in Figure 1 consists of a microphone mounted in the CNC ProTurn 9000 machine tool post and a computer with a wear detection system application running on matlab software. The data stream of the signal from sound recording to the noise wear classification process is shown in figure. 2.

![Figure 1. experimental setup of on-line tool wear detection.](image)

![Figure 2. Data flow and data processing in on-line tool wear detection](image)

The tool used in this research is carbide tool with type DCMT070204. Wear of tool is measured using Nikon Measurescope. The observation tool used in this research is shown in Figure 3. The picture shows the normal tool and worn tool according to ISO3685 criteria used in this research. the tool is used for ST42 cylindrical steel machining.
Figure 3. Microscopic photos of normal tools and wear tools according to the ISO3685 tool wear criteria used in the study

Sound signal recording using omni-directional Andoer microphone with frequency response between 20Hz to 16 kHz. Sound recording is done in matlab software as well as signal conditioning in the form of normalization of sound amplitude. The next step is a fast fourier transform to get the frequency spectrum of the sound signal. Based on the frequency spectrum data is selected frequency feature that characterizes the wear of tool. Selection of features using correlation analysis to look for features of a strongly correlated frequency against tool wear grade. The next stage is to train artificial neural networks in order to distinguish signals derived from normal tool or from worn tool.

4. Results and discussion

Results of correlation analysis of the frequency spectrum against the wear grade of the tool are shown in Figure 4. (a). visible from the picture there is no frequency spectrum feature that is very strongly correlated with the wear grade. It is also seen that the high frequency spectrum is stronger in correlation than the low frequency spectrum. With strong correlation coefficient criteria above 0.4, 33 features were selected for artificial neural network input, figure 4. (b).

The selected feature of 33 out of 110 recording data is entered in a multi layer perceptron neural network with 33,16,1 neuron architecture. A total of 110 data is divided into training data, test data, and validation data, with a proportion of 8: 1: 1. Multi layer perceptron trained with back propagation method. Training parameters used are default matlab with stopping criteria of training process if reach MSE 0.001 and 10 times validation check. The best training results are shown in Figure 5. The best
results are achieved on the 34th epoch with the stopping criteria of 10 validation checks. Accuracy achieved by classifier is equal to 76%.

![Best Validation Performance is 0.76077 at epoch 34](image)

**Figure 5.** The best training results.

5. Conclusion
The DCMT070204 tool wear detection system has been developed successfully. This detection system records machining sounds and then the sound signals are transformed in the frequency domain to select the frequency feature that characterizes the wear of the tool. The selected frequency feature is used to train artificial neural networks. The results of artificial neural training to distinguish worn tool and normal tool can achieve accuracy of 76%.

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