Tool Condition Monitoring Using Spectral Subtraction Algorithm and Artificial Intelligence Methods in Milling Process

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***Abstract*—Process monitoring is necessary in machining operation to increase productivity, improve surface quality and reduce unscheduled downtime. Tool wear and breakage are important and common sources of machining problems due to high temperatures and forces of machining process. Therefore, it is highly beneficial to develop an online tool condition monitoring system. This paper investigates a robust tool wear monitoring system for milling operation. Spindle current is employed as the fault indicator due to its cost-effectiveness and ease of use in an industrial environment. Wavelet time-frequency transform is used as a superior tool to simultaneously investigate time-varying characteristics of the signal and its frequency components. After the time-frequency step, spectral subtraction algorithm is employed to intensify the effect of tool wear in the signal and reduce the effect of other cutting parameters. Based on this method, the average signal spectrum of a healthy case is subtracted from all the signals with the same cutting parameters. After further processing and noise reduction, fault features and indicators are extracted from the results of the processed signal. Finally, five advanced machine-learning algorithms are implemented for modeling the system. Gaussian process regression, support vector regression, Bayesian rigid regression, nearest neighbor regression and decision tree methods are compared. The methods are validated based on the experimental data. Results show a high accuracy for the tool wear estimation while decision tree method was superior to others with accuracy of 91.6%.**

***Index Terms*—component, CNC Machines, automation, tool condition monitoring, artificial intelligence**

I. Introduction

Machining processes are fundamental in today's manufacturing industries. There is a growing demand to make the machining operation automatic to increase productivity. Tool defects can be considered as one of the most common and costly faults of machining process. Due to the contact forces and friction between cutting tool and workpiece, high temperature in the cutting area and pressure of the chips on the tool, some defects may happen to the tool which deteriorates the surface finish or cause damage or breakage to the tool, workpiece or machining center [1]. Therefore, it is in high demand to design a reliable and robust online automatic TCM system to improve accuracy, reduce production costs and increase productivity.

TCM methods can be categorized into two main groups: direct and indirect methods. Direct methods use actual measured value of fault with sensors such as laser, optical and ultra-sonic sensors. However, in indirect methods, physical parameters of the system such as force, vibration etc. are utilized to represent tool condition, indirectly [2]. Although direct measurement methods estimate tool fault with high accuracy, they are still expensive and not suitable for online applications in industrial environment. However, indirect methods can be used to fulfill purpose of TCM as an alternative with accurate results and acceptable cost by using a proper descriptor signal and an appropriate modeling method [3]

Signals, which are most widely used for tool condition monitoring include: Force, vibration, acoustic emission, current and power signals. Force signal shows promising behavior to represent tool wear variations during the machining process, however, it is highly dependent on other operating conditions and to use in industry. Acoustic emission and vibration sensors are also very practical to use in industrial environment. For example, in an study by Gangadhar et al., condition of a single point cutting tool is monitored with help of the vibration signals acquired from an accelerator [4]. Soltani Rad et al. also employed current of the spindle motor sensors as an economic and practical indicator signal and achieved acceptable results for monitoring of the tool flank wear condition [5].

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After choosing appropriate sensors and signal acquisition, the signals should be processed to reveal the effect of monitoring variables and remove noises. Time domain analysis, frequency domain analysis and time-frequency domain analysis are three common approaches for signal processing stage[6]. Based on the non-stationary nature of faulty signals, time-frequency analysis can provide rich information about machinery health conditions. Therefore, discriminative fault features can be extracted from a faulty signal as it considers frequency domain and time domain information at the same time [7]. Safizadeh et al. studied short-time Fourier transform, the Wigner-Ville distribution and the wavelet transforms as three methodology for mechanical fault diagnosis [8]. Wavelet transform is a superior time-frequency transformation method, which is applied in machining monitoring. Li XL et al. investigated tool wear using wavelet packet transform for generating features from AE signal complimented by a fuzzy clustering method (FCM) for decision-making. In another study, Li XL et al. employed discrete wavelet transform for tool breakage monitoring [9], [10]. Wavelet is also employed in chatter detection. Shin et al. implemented a wavelet-based maximum likelihood (ML) estimation algorithm for on-line chatter detection [11].

The output of time-frequency domain has high dimensions. Therefore, after time-frequency analysis, this information should be converted to the appropriate feature vectors to make the monitoring problem solvable. Dimensionality reduction methods such as principal component analysis (PCA) and least square analysis (LSA) are popular among the literature to perform this task. Chen et al. compared the results of a least square support vector machine based algorithm with dimensionality reduction using PCA and LSA and without these methods [12].

Spectral subtraction is another method which can be implemented to enhance the signal quality. It is originally used in speech enhancement to remove the effect of steady sounds in the environment [13]. This method can also be employed in fault diagnosis applications to present fault indicators. For example, El Bouchikhi et al. proposed an algorithm for fault diagnosis of induction machine bearings using spectral subtraction method. In this study, stator current frequency response of the healthy machine is subtracted from the spectrum of machine current acquired signal to present better fault indicators [7].

During the machining process, many parameters such as depth of cut, feed rate and workpiece material changes which may degrade the monitoring system performance and reduce system robustness. Therefore, a model between the prepared feature vectors and tool condition should be developed with an ability to represent non-linear complex systems. Many methods such as artificial neural networks, Fuzzy logic, Neuro-fuzzy, support vector machine (SVM) and Bayesian networks are employed to perform this task in the literature. For example, particle swarm optimization algorithm is combined with support vector machine to develop a hybrid algorithm for tool flank wear estimation in milling operation [14]. While these methods are individually being implemented and used in the literature, a comparative study between them could be beneficial for researchers in this domain.

In this study, a TCM system is developed based on current signal of spindle motor as the fault indicator signal. Wavelet time-frequency analysis method is employed for signal processing step. After the wavelet analysis, spectral subtraction method is applied around tooth path frequency. In the next step, Gaussian process regression, support vector regression, Bayesian rigid regression, nearest neighbor regression and decision tree methods are implemented to learn a model between tool wear behavior and signal indicators. This paper is organized as follows: Section II represents the methodology of the monitoring system. Backgrounds and formulation of the methods which are used in this paper are explained in section III. Section IV introduces the benchmark dataset for validation of this work. Results and discussion are presented in section V and section VI is dedicated to conclusion.

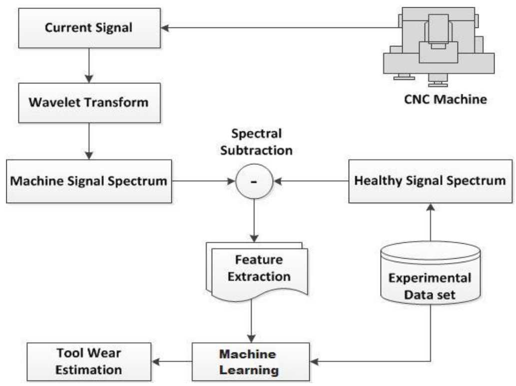

Figure 1. Methodology diagram

II. Methodology

This study investigates tool wear monitoring using time-frequency transformation, spectral subtraction and machine learning. Fig. 1. depicts the monitoring system's methodology diagram. The fault descriptor of this research is current signal based on its high performance and applicability in industrial environment. After acquisition of signal; it will be transformed to time-frequency domain. Using experimental data, an estimate of the spectrum of healthy signal for different cutting conditions is obtained. Afterwards, it is subtracted from each new signal under same cutting conditions. It helps to intensify the effect of fault and remove the steady state part of spectrum for normal situation. Finally, a machine learning method is used to model the system using experimental dataset.

III. Background of Techniques

A. *Wavelet Transform (WT)*

Wavelet transform is one of the methods that are widely used for health condition monitoring systems in

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the literature. In WT, wavelets are used as the basis instead of sinusoidal functions that are used in Fast Fourier transforms (FFT). It is an effective tool for transient signal analysis as well as time-frequency localization since; it adds a scale variable in addition to the time variable in the inner product transform. It has a better time localization but a lower frequency resolution for higher frequency components. In contrast, for lower frequency components, the frequency resolution is higher while the time localization is worse. Following equation describes the formulation of the continuous wavelet transform for signal $x(t)$ [15].

$$WT_x(t,a) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(u)\psi\left(\frac{u-t}{a}\right) du \quad (1)$$

where wavelet $\psi((u-t)/a)$ is derived by dilating and translating the wavelet basis $\psi(t)$ and $1/\sqrt{a}$ ($a > 0$) is a normalization factor to maintain energy conservation.

B. Spectral Subtraction

Spectral subtraction is a method which was originally used for speech signal enhancement. A signal is considered a combination of noise and clean speech; therefore, the noise spectrum is estimated during speech pauses, and an estimation of the noise spectrum is subtracted from the noisy speech spectrum to obtain the clean speech. It can be employed in fault diagnosis applications by removing the steady state and normal process spectrum from the new signals to obtain their anomalies and fault signatures. Consider a measured signal which consists of the steady state normal component and additive fault [7]:

$$y[n] = s[n] + d[n] \quad (2)$$

where $y[n]$, $s[n]$ and $d[n]$ are the sampled measured signal, fault and steady state component, respectively. The frequency domain representation of the signal is given by:

$$Y(j\omega) = S(j\omega) + D(j\omega) \quad (3)$$

Therefore, the fault component of the signal can be obtained based on the following equation:

$$\hat{S}(j\omega) = Y(j\omega) - \hat{D}(j\omega) \quad (4)$$

where $\hat{S}(j\omega)$ is the fault related spectrum estimate and $\hat{D}(j\omega)$ is estimate of steady state component of spectrum. $\hat{D}(j\omega)$ often is obtained using the time-averaged signal spectrum using the normal healthy state of the system:

$$\hat{D}(j\omega) \cong |\bar{D}(j\omega)| = \tfrac{1}{K}\sum_{i=0}^{K-1} |D_i(j\omega)| \quad (5)$$

IV. Experimental Dataset

NASA Ames and UC Berkeley milling dataset is used for validation of the research [16]. The experiments are performed under various operating conditions using the Matsuura MC-510V machining center. In this research, current sensor of spindle is selected based on its ease of use and practicality in industrial applications. The dataset signals include cases with changes in depth of cut, feed rate; therefore, a system will be developed under varying cutting parameters.

The tool is a 70 mm face mill with 6 KC710 inserts and workpiece material is cast iron. A OMRON K3TB-A1015 current converter feeds the signal from one spindle motor current phase into the cable connector and a model CTA 213 current sensor (Flexcore Div. of Marlan & Associates, Inc.) is used for data acquisition. Flank wear (VB), which is defined as the distance from the cutting edge to the end of the abrasive wear on the flank face is considered as the fault and its value is reported in all the experiments using a microscope

V. Results and Discussion

After signal acquisition, signals should be processed to extract better fault indicators and remove noises. Signals are transformed to time-frequency domain as the first step of the processing using Morlet Wavelet transform method. Fig. 2 represents the result of the wavelet transform. The diagram represents the WT output for the healthy signal (VB=0) as well as four states of the fault. Based on the graph, there are high magnitudes around tooth pass frequency. As fault value increases, the magnitude and density of wavelet values increase. The data is still noisy and needs further processing to extract informative features.

Afterwards, spectral subtraction is applied to the signals. For this purpose, an average estimation of the current signal spectrum for each healthy case is extracted. For a new signal, the estimated healthy spectrum under the same cutting conditions is subtracted from the signal. It can help to normalize the signals based on their cutting conditions and magnify the effect of tool wear by removing steady state components of the signal in normal situations. Fig. 3 represents the result of spectral subtraction for different states of the fault. Based on the diagrams, for the healthy state, signal has zero or low magnitudes for most of the regions. As the fault develops, the magnitude of spectrum, especially around tooth passing frequency, increases. The effect of fault and its progress is clearer in this graph compared to the previous representations (Fig. 2).

Further noise canceling and signal refinement is performed after spectral subtraction step. Kurtogram analysis based on the approach of Antoni et al. [17] is performed and a local region around 125 Hz is selected (tooth pass frequency) for further analysis. Fig. 4 depicts the signals after further processing and denoising. As it can be seen from the graphs, tool wear signature is clear in the signals and therefore signals are ready for the feature extraction step.

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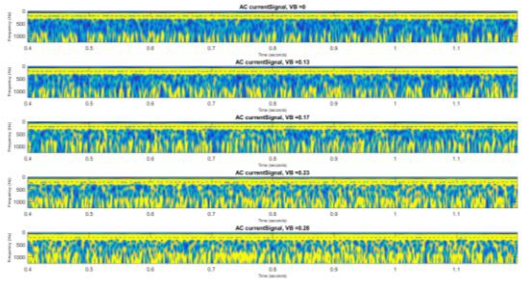

Figure 2. Wavelet representation of the signals with different VB levels

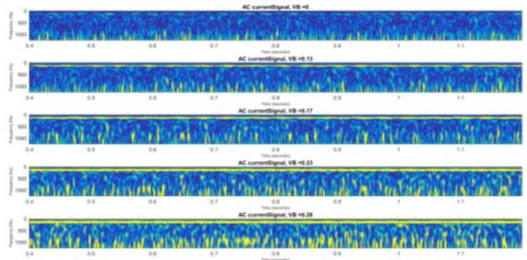

Figure 3. Wavelet representation of signals after spectral subtraction for different levels of VB

In the next step, various features are extracted from each signal. Lower band of signal, upper band of signal, maximum magnitude and frequency of its occurrence, variance, standard deviation and width of frequency response are among the extracted features. Fig. 5 shows lower and upper band of the signal and width of the frequency response.

Changes in the cutting parameters such as depth of cut, feed rate and workpiece material may affect the features, which makes defining a model for the machining monitoring more challenging. Generally, having more variables makes the system more complex to model. Therefore, a model with ability to learn multidimensional non-linear relationships is necessary for the next step.

Various machine learning and regression methods are employed as the last step for modeling the system. Experimental data is used to construct a dataset of feature vectors with their corresponding fault values. 80% of the dataset samples are devoted to training step, and 20% are reserved for testing. Average accuracy in percentage and RMSE) are calculated as the representative of the performance. Table I presents results of the experiments for the system using the test dataset. The systems are trained and tested under varying cutting parameters.

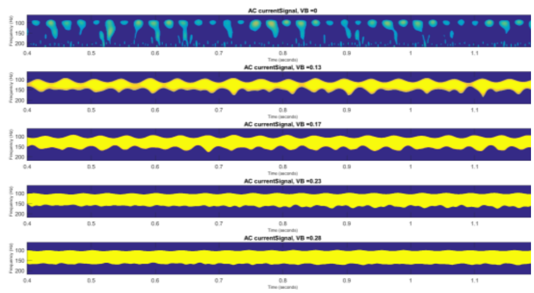

Figure 4. Signal representation after noise reduction for different VB values.

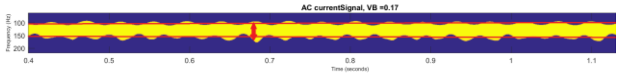

Figure 5. Extracted features of the signals

Based on the results, decision tree regression method is Shows the better performances in our study with 91.6% accuracy in tool wear estimation. Bayesian rigid regression and nearest neighboring methods are also promising with 90.8% and 88.4% accuracy respectively. In general, all the methods provide acceptable accuracy (minimum for Gaussian process regression with 77.0% accuracy) which shows the robustness and high distinctiveness of the features in fault representation. RMSE is lowest for Baysian rigid regression (0.0872) and almost similar to decision tree method RMSE (0.0877). Highest RMSE value belongs to Gaussian process regression with value of 0.2301. Fig. 6 also depicts a comparison between the machine learning methods.

TABLE I. Comparison Between Accuracy and RMSE of Different Regression Methods

Regression Algorithms	**Average Accuracy %**	**RMSE**
Gaussian Process Regression (GPR)	77.0	0.2301
Bayesian Ridge Regression	90.8	0.0872
Nearest Neighbors Regression (KNN)	88.4	0.1131
Support Vector Regression (SVR)	82.6	0.1675
Decision Trees Regression	91.6	0.0877

VI. Conclusion

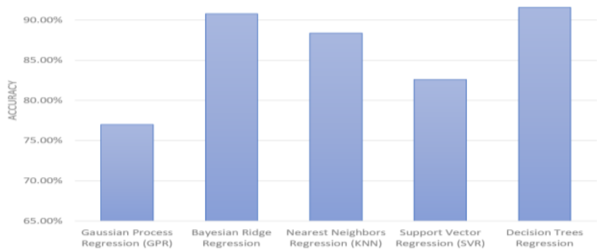

Figure 6. Results of machine learning methods

In this research, tool condition monitoring under changing cutting parameters was investigated. A system is designed and developed for tool wear estimation which consists of: 1-Spindle current signal as a practical fault indicator, 2-An advanced time-frequency transformation method called Wavelet transform due to its great applicability to process signals and reveal rich information in both time and frequency domain simultaneously, 3-Spectral subtraction method to remove the effect of normal operation from the signal and intensify the fault signature which helps to extract the most discriminative and relevant features to the fault and 4-Advanced machine learning methods to model the relations between the signals and their corresponding fault values. These methods are implemented to construct a model and estimate tool wear for new inputs based on the defined model. The algorithm proposed by this research showed accurate results with accuracy of up to

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91.6% for tool condition monitoring with a promising ability to tolerate and work under changing operation conditions.

Wavelet analysis revealed the time variant characteristics of frequency response of the signal and is beneficial in revealing fault characteristic of the signal. Therefore, this study confirms its performance and applicability for this application. The spectral subtraction method also contributed highly in revealing the fault signature of the signal. This method removed the steady state part of the signal due to normal cutting and magnified remaining fault characteristics proved its applicability and high performance in the processing step of the system.

The final step was a comparative study between state of the art machine learning methods for modeling the system. The robustness of the system and its performance using different methods are investigated. The results endorse the proposed methodology for wear estimation as all the systems had satisfactory accuracy for industrial applications. Decision tree method and Baysian rigid regression have the highest accuracy (91%) for the test data set. Lowest RMSE belongs to Baysian rigid regression and Decision tree methods. The highest RMSE is observed for Gaussian process regression.

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