AE signature analysis using continuous and discrete wavelet transforms to predict grinding wheel conditions

K Shivith and K Rameshkumar

1 Department of Mechanical Engineering, Amrita School of Engineering, Coimbatore – 641112, Amrita Vishwa Vidyapeetham, India

Abstract. In this study, experiments were conducted in a surface grinding operation to acquire and analyze the AE signature to establish a statistical correlation between Acoustic Emission features extracted in wavelet domain with grinding wheel conditions. Grinding wear plot was established to identify the grinding wheel conditions by monitoring the wear in the abrasive grinding wheel and workpiece. Continuous and Discrete Wavelet transforms were carried out to extract the wavelet coefficients. Decision Tree based statistical models were built using discrete and continuous wavelet coefficients. The performance of J48 Decision tree and Classification and Regression Decision Tree (CART) are compared using the classification accuracy and kappa statistics measures. In discrete wavelet transforms, wavelet coefficients are extracted using four mother wavelets namely Haar, Daubechies, Symlet, and Coiflet. In Continuous Wavelet Transforms, the Morlet wavelet is used to extract the 1D wavelet coefficients using 2D scalograms.

1. Introduction

1.1. Tool Condition Monitoring (TCM) Framework

Tool condition monitoring is an indirect way of studying the tool wear and identifying the condition of the tool using the data acquired during the machining process. The tool wear may be due to many reasons like abrasion, adhesion, fatigue, dissolution, and tribo-chemical mechanisms. The tool wear or tool conditions are difficult to quantify during the process. Generally offline methods are applied to measure the tool wear and the cause for the same. In automated environments, it is essential that tool conditions need to be monitored and decisions to be taken without any manual intervention. Sensors play a vital role in TCM to capture the condition of the tool due to various failure mechanisms takes place during the machining process. Different types of sensors are available for identifying condition of the tool during the machining process. Some of the sensors that are commonly used in the tool condition monitoring process are dynamometers (for measuring force signal), vibration sensor (for measuring vibration signal), acoustic emission sensor (for measuring AE signal), temperature sensors, current sensors, optical sensors, and load cell. These sensors are used to capture the data from the machining process which will have the information about the tool wear or tool failure mechanism. The data collected by the sensor must be processed and for this, the signal processing technique is used. Features containing the useful knowledge about the tool conditions are extracted and statistical models are built using machine learning classifiers. A typical grinding wheel condition monitoring framework is shown in Table 1.
Table 1. Grinding wheel condition monitoring framework

| Machining Process | Signal Acquisition / Sensors | Signal Processing Domain | Statistical Models (Classifiers) | Grinding Wheel State |
|-------------------|-----------------------------|--------------------------|---------------------------------|---------------------|
| Grinding          | • Dynamometer               | • Time Domain            | • Decision Trees                | • Sharp – Initial condition |
|                   | • Acoustic Emission Sensor  | • Frequency Domain       | • Fuzzy Logic                   | • Intermediate steady-state condition |
|                   | • Load cells                | • Time-Frequency Domain  | • Neural Net                    | • Worn-out condition |
|                   | • Motor Current sensors     | (Wavelet)                | • Naïve Bayes                   |                      |
|                   | • Infrared sensors          |                          | • Support Vector Machines       |                      |
|                   | • Ultrasonic Sensors        |                          |                                 |                      |

1.2. Acoustic Emission (AE) based Tool Condition Monitoring (TCM)

TCM is getting enormous recognition in industries nowadays due to the increased automation activities. The automation leads to increased production and reduced lead time. Moreover, in a machining processes it necessary that manual intervention to an extent need to be reduced for making decision relevant to tool replacement or repair. TCM will support the decision makers to utilise the tool effectively and efficiently without over-using and underutilizing. Thereby, the shopfloor decision maker will have a better control over the tool and effectively plan their maintenance activities and avoid catastrophic failures and quality issues. In TCM, many sensors are being used to detect the change in conditions of the tool for developing an effective TCM system. Choice of a sensor is a crucial step in the development of a TCM system. There are plenty of sensors available to detect the conditions of the tool in the machining processes such as turning, milling, drilling, and grinding etc. Some of the signatures of the cutting processes which are effectively correlated to the tool conditions are cutting force, vibration, acoustic emission, temperature, spindle current etc. The right sensor must be chosen based on the mechanism of the cutting process. The cutting tools used in the machining processes are designed for set of criterions such as metal removal rate and quality of the surface generated on the workpiece. The choice of sensors is mainly based on a) detectability of the change in condition of the tool, b) range, and span of the sensor, c) frequency range, etc.

Detailed studies have been made by researchers for selecting a suitable sensor for a typical manufacturing process. Variety of sensors have been tried in many metals cutting process namely turning, milling, drilling, and grinding. Even though there is a similarity in metal removal mechanism in these processes, but the amount of material removed in terms of chip thickness is different in these processes. The manufacturing processes can be classified into macro, micro, precision and ultra-precision and nano machining processes. In these processes the amount of chip thinness produced during the machining operation is different. While monitoring the cutting processes in these scenarios, all the sensors does not have same performance in detecting the changes in the tool conditions. Dornfeld et al. [1] observed various sensors namely encoders, vibration sensors (accelerometers), acoustic sensors and optical sensors. It is concluded in their study that piezo electric sensors (acoustic emission) have better accuracy in predicting the conditions in a precision cutting process. Better performance of AE sensors was observed compared to force, load, optical and vibration sensing sensors in a precision machining environment.

The good performance of AE sensors in precision machining process such as grinding are due to a) high sensitivity, b) identifying the defects, and failure modes at early stage c) capturing the signals in a higher frequency range (1kHz to 1MHz) d) suitability of AE based technique for real-time monitoring e) avoidance of machine disturbances taking place at lower frequencies and d) high signal-to-noise ratio. AE sensor also has a swift retort to the transitory performance of the precision machining process such as grinding. During the grinding process, AE activities such as abrasive particle wear, fracture of bonding material in the grinding wheel, thermal burns, loading and glazing etc are captured by the AE sensors in the higher frequency range without disturbing the machine vibrations due to environmental effects.
1.3. Motivation
Tool condition monitoring has now become important in every manufacturing industry. As automation has taken over the industry, tool condition monitoring has been an indispensable part of it. In such a scenario, the manufacturing industry with a variety of processes involving a variety of tools needs an efficient TCM system. The condition of the tool has a direct influence on the quality of the product being produced. It is important to maintain a good condition of the tool otherwise reliability of the product will be questioned in the market. This thought leads us to develop a good tool condition monitoring model that can predict the condition of the tool using the sensor information.

In this study, we are developing statistical models from the AE signal extracted from the grinding wheel using both the Discrete and Continuous wavelet transforms. The wavelet transforms are found to give better time and frequency resolution at the same time. Studies on building a statistical model using AE wavelet features are limited in the literature. An effort is made in this research paper to foretell the grinding-wheel condition using AE wavelet features extracted with the help of discrete and continuous wavelet transforms.

1.4. Literature Review
For developing an TCM using AE sensors, a comprehensive literature review was conducted focusing on AE signatures and their applicability in predicting the grinding wheels conditions using the machine learning models. The sensor selected for TCM of grinding process should reveal the change in the condition of the abrasive wheel. Importance of AE sensors in precision machining operations are available in [1, 2]. Liao et al. [3] developed Hidden Markov Models (HMM) using wavelet features. Clustering methods were adopted to categorize the grinding-wheel conditions. Teti et al. [4] studied machining operations and found out the advantages of using AE sensors in tool condition monitoring in micromachining processes.

A review on TCM focusing on sensors in signal acquisition, signal processing and modelling pragdiasms in milling, grinding, turning and drilling operations was presented bt Roth et al. [5]. Dressing operation in a grinding process is monitored using AE signals with the aid of Artificial Neural Networks by Moia et al. [6]. AE signature features are extracted, and a grinding wheel dresser was classified as 'dull' and 'sharp' in their study. In a cylindrical grinding process, Support Vector Classifiers (SVM) built with AE features performing well related to vibration features [7]. Mouli and Rameshkumar [8] carried out an AE signature analysis in surface grinding operation by acquiring time-domain AE features using CART algorithms. Grinding wheel conditions were predicted using Hidden Markov Models (HMM) by Krishnan and Rameshkumar [9]. AE signatures were used for building the HMM models. Chen et al. [10] studied the grinding burn using wavelet packet transforms using AE signature and found that AE is predicting the grinding burn with good accuracy. Machine learning classifiers are constructed using ensembles with wavelet features and abrasive-wheel conditions are classified [11]. Worn-out and good conditions of a abrasive wheel are studied in [12] considering various metal removal conditions using AE based wavelet approach.

Degradation assessment of a grinding wheel was studied by Benkedjouh et al. [13] using wavelet transforms. Krishnakumar et al. [14] studied AE and vibration features for TCM of high speed machining process. Macine learning models were built using the wavelet coefficients of AE and Vibration signatures. It was obserbed that wavelet features of AE has better resolution in predicting the tool conditions compared to vibration features of AE. Machine learning models built with fused features in time, frequency and wavelet domain are giving better classification accuracy [15] in tool condition monitoring of high speed precision process. Off late, Alexandre et al. [16] proposeds a fuzzy method using AE features for monotoring the grinding process. Xiao et al. [17] suggested an AE based wavelet entropy-based algorithm used to select the optimal wavelet in a condition monitoring problem.

From the literature review, it is concluded that the AE sensor is best suited for detecting failure modes in precision manufacturing processes. AE emissions in grinding process are due to the change in conditions of the grinding wheel and are taking place at higher frequencies. AE sensor will be able to capture the high frequency transient signature of the process. After the signal acquisition, signal processing is carried out to identify the conditions of the abrasive wheel.
TCM of the grinding process is one of the emerging areas of research due to the increased automation of the grinding processes. Automation needs intelligent techniques for taking decisions without any manual intervention. Condition monitoring using sensors will lead to the effective utilization of the grinding wheel. In machining processes such as grinding, AE sensors are predicting the tool conditions with good accuracy. Machine Learning statistical classifiers were built for predicting the tool conditions using features extracted in time, frequency, and wavelet domains. Time domain and frequency domain features are frequently used by the researchers to build classifiers using ML classifiers such as decision trees, SVM, ANN, etc. Very limited studies focused on ML classifies trained using wavelet coefficients for predicting grinding wheel conditions. Decision tree algorithms are simple and from the decision tree, simple If-Else rules can be generated for developing an on-line TCM system.

2. Objective and Methodology

2.1. Objectives
The objectives of this study are as follows.
- Identifying conditions of the abrasive wheel by conducting experiments
- Extracting wavelet coefficients by performing AE signature analysis in continuous and discrete wavelet domains.
- Building statistical classifiers using decision tree J48 algorithm and CART for predicting the conditions of the abrasive wheel.

2.2. Methodology
The idea in this study is to extract the AE data of the grinding wheel for the complete cycle and use that data to classify using different classifiers and identify the Sharp, Intermediate, and Dull conditions. The methodology adopted in this study is given as follows:
- Establishing an experimental set-up to identify grinding wheel conditions
- Acquire AE signature
- Selection of wavelets
- Signal Decomposition in Discrete and Continuous Wavelet Domains
- Wavelet coefficient extraction in the discrete and continuous wavelet domain
- Training machine learning classifier (Decision Tree J48 algorithm and CART) using wavelet coefficients extracted in the discrete and continuous wavelet domain
- Prediction of grinding wheel conditions

2.3. Experimental Setup
An auto-feed grinding machine was used to collect the data. The AE sensor is fixed to the workpiece. The stress waves generated due to the change in tool conditions during machining are captured. ‘Micro 30 D’ AE sensor with functional frequency of 100 to 350 kHz is utilized for acquiring the AE. The grinding wheel is made of Aluminum Oxide and workpiece is made up of Medium Carbon Steel. The experimental setup is as shown in Figure 1.
The set-up for conducting experiment consisting of a) Surface grinder b) Grinding wheel attachment for capturing AE signals, AE sensor, Preamplifier, DAC, AE-Win software for extracting features from the AE signature, Machine learning classifiers, and computer for data processing and data presentation. In the workpiece, the AE sensor is fixed. The output from the sensors is fed to the pre-amplifier. The amplified signal is fed to the Data Acquisition System (DAQ). From the DAQ the signal is converted into time domain signature (time Vs amplitude). AE-Win software is used to extract the AE features. Machine learning classifiers will provide the condition of the grinding wheel after training using the AE features. The grinding wheel is subjected to ground the mild steel workpiece. Experimentations were performed with a grinding speed of 2500 rpm, a feed rate of 0.03 mm, and a depth of cut of 0.05 mm. These cutting parameters are set with the objective of maximizing the grinding wheel life. The sensor used in the acquisition of signal consists of the piezoelectric transducer of differential type “Micro 30D” is fixed to the workpiece. AE sensor has a frequency response range of 100 – 300 kHz.
The sensor another end is attached to Pre-amplifier. The pre-amplifier another end is attached to Computer. Signals are extracted from the sensor and stored in the computer for signal processing. Feature extraction and signal processing are done in AE-Win software. For experimentation, a sampling rate of 1MSPS and a threshold of 25DB is used to collect the data. AE-Win software is used in this study for waveform processing, data storage, and display of feature date and reply of the data.

3. Grinding Wheel Conditions
In any TCM problem, first, it is necessary to identify the various tool conditions to be predicted by the statistical model. In an abrasive process such as grinding, abrasive wheels are used as tool to ground the workpiece to the required finish. After the few cycles of grinding operation, the abrasive grinding wheel loses its cutting property due to a) wear of the abrasive particles, b) failure of bond material and c) loading and glazing of the abrasive wheel. To continue the process, the abrasive wheel must be dressed for exposing the new abrasive grains. In a typical grinding cycle initially grinding wheel will have sharp abrasive particles. During the machining process, sharpness of the abrasive grains will gradually lose its sharpness and become dull or worn-out. In the dull or worn-out condition, the abrasive wheel must dress to regain its cutting ability. In general, grinding wheel has three states namely, a) sharp abrasive condition where the wear rate of the grinding wheel abrasive particle and work piece wear is very high b) intermediate condition where the equilibrium steady condition is established where wear rate in the grinding wheel is less and wear rate is more in the work piece and c) worn-out condition where wear in the grinding wheel is more and wear in the work piece is less. The grinding wheel life is mainly depending on the intermediate condition where the uniform wear takes place in wheel and workpiece. At the end of the steady state condition (intermediate state), or in the beginning of the third state (worn-out condition) the abrasive wheel must be sent to dressing operation to regains its cutting ability.
Experimental approach is followed in this work to identify the grinding wheel conditions. The wear of the abrasive wheel and work piece is monitored continuously during the grinding process at various intervals of time. The weight loss in the workpiece and grinding wheel are plotted to get the grinding wheel wear plot as shown on Figure 2. From the slope of the wear plot (rate of change of wear), the grinding wheel conditions are identified. Wear data is recorded for the complete grinding cycle starting from sharp abrasive wheel condition to the worn-out condition of the tool. Three distinct zones namely sharp, intermediate, and worn-out states are identified from the wear plot. It was identified that the initial state of the grinding wheel is up to 7 passes of grinding operation. The intermediate state corresponds to pass 8 and 45. The grinding wheel lost its cutting ability after the pass 52 and identified as the worn-out condition.

4. Wavelets Coefficients Extraction in Discrete and Continuous Wavelet Domain
Wavelet based methods are used to analyse the sensor signatures in time-frequency domain. The important issue in wavelet transform is to identify the most optimum mother wavelet for the given tasks. The information content in the wavelet coefficients are not the same for all the wavelets. The time-domain signal is transformed into time-frequency domain using discrete and continuous wavelet transforms. Wavelet coefficients are extracted after decomposing the signal using the chosen wavelet. These wavelet coefficients carry information regarding the condition of the grinding wheel. Mother wavelets are characterized by properties such as compact support, orthogonality, symmetry, and vanishing moments. The mother wavelet chosen in this study for DWT is Haar, Daubechies, Symlets, and Coiflets. For CWT, the most preferred wavelet is the Morlet wavelet which is considered in this study.

4.1. Signal Decomposition in Discrete and Continuous Wavelet Domains
The DWT decomposes the signal, into a series of wavelet coefficients. multi-level wavelet decomposition is carried out to extract the discrete wavelet coefficients for all the mother wavelets considered in this study. In DWT, the AE signature is passed through a series of high pass and low pass filters for the signal decomposition. For improving the frequency resolution, multiple levels of decomposition are carried out. Decomposition is carried out using the AE signatures of sharp, intermediate, and worn-out conditions of the grinding wheel separately. In this study, it was found that two levels of decomposition produced better resolution. Decomposition is carried out for all the conditions of the grinding wheel using all the mother wavelets considered in this study. The decomposition of the dull condition signal after 2 levels of decomposition using Coiflet wavelet is shown in Figure 3. Similarly, for sharp, intermediate, and worn-out conditions, decomposition is carried out and wavelet coefficients are unearthed.

Figure 3. Decomposition of dull condition signal using Coiflet wavelet
In CWT, the values of scaling and translation factors are continuous. So, the output of the one-dimensional signal will be 2-Dimensional scalograms. From the 2D scalograms, ID features are extracted and given as an input to the J48 and CART classifiers. As an example, the Sharp grinding wheel condition scalogram obtained using the Morlet wavelet is shown in Figure 4. Similarly, scalograms of intermediate and worn-out conditions are plotted. From the scalograms, wavelet coefficients are extracted to train the J48 and CART algorithms.

5. Statistical Modelling and Performance of decision tree algorithms
A decision tree is a supervised learning classifier that divides data recursively using discrete or continuous data for classification or regression. The various algorithms used in the decision trees included ID3, C4.5 / J48, CART, C5.0, CHAID, QUEST, CRUISE, etc. Among these algorithms ID3, C4.5 and CART are quite popular. ID3, or Iterative-Dichotomizer (ID3), was the first decision tree algorithm proposed by Quinlan [18]. In ID3, the splitting criterion is used in information gain/entropy. ID3 handles only the categorical data and pruning is not possible. Also, ID3 is susceptible to outliers. Classification and Regression Tree (CART) algorithm handles both numerical and categorical data. Pruning can be done in CART and handles the outliers. The improvised version of ID3 is C4.5. C4.5 implementation in Java is called as J48 [19]. The advantages of J48 include a) handling continuous and discrete data, and b) the use of pruning to solve over-fitting issues. In this study, CART and J48 decision tree algorithms are used to build the statistical models using continuous and discrete wavelet coefficients. In the CART algorithm three variants viz. simple, medium, and complex decision trees are trained with wavelet coefficients.

The AE signature from the grinding wheel for the whole cycle was taken and the signal was analysed in the time-frequency domain by extracting wavelet coefficients in both DWT and CWT. In DWT, wavelet coefficients were extracted using the mother wavelets of Haar, Daubechies, Symlet, and Coiflet. In CWT, 2D scalograms were developed considering the sharp, intermediate, and worn-out conditions of the grinding wheel. From the 2D scalograms, ID features are extracted to train the classifiers. For CWT, Morlet wallets are used to generate the scalograms. J48 and CART statistical classifier models are built using the features extracted from DWT and CWT. Performances of the classifiers were compared by computing classification accuracy, and Kappa statistics. 10-fold cross-validation is performed to estimate the efficiency of the statistical model in predicting the condition of the grinding wheel.

5.1. Performance of classifiers
Classification accuracy of classifiers are computed using wavelet coefficients extracted in DWT and CWT domains are shown in Figure 5. Kappa statistics of classifiers are arrived using wavelet coefficients extracted in DWT and CWT domains are shown in Figure 6. Classification accuracy is the ratio of correctly classified instanced (data points) by the classifier to the total number of instances used.
for training and testing the classifier. Kappa measure will provide how good the model is performing over the performance of a model that simply guesses at random based on the frequency of each class. All the wavelets which were used with DWT and CWT are classifying the condition of the grinding-wheel with good precision. It was found that the Coiflet and Daubechies wavelets are effective in classifying the grinding wheel condition in DWT using a J48 classifier with a classification accuracy of 95.70% and 95.30% respectively. Compared to DWT, the CWT using Morlet wavelet giving a better accuracy of 97.06% and making it an effective model for predicting the grinding wheel conditions. CART-complex tree trained with Morlet CWT features produces the maximum classification accuracy. This is due to the continuous values of scales and translation factors taken up by the transform while decomposing the signal. The kappa value also confirms the CART-Complex tree classifier as a good classifier.

![Figure 5](image5.png)

**Figure 5.** Performance of Classifiers – Classification Accuracy

Note: Coiflet, Daubechies, Symlet and Harr wavelets are used in DWT. Morlet is used CWT

![Figure 6](image6.png)

**Figure 6.** Performance of Classifiers – Kappa Statistics

Note: Coiflet, Daubechies, Symlet and Harr wavelets are used in DWT. Morlet is used CWT
6. Conclusions and Future Scope
In this study, it is observed that AE features extracted in the wavelet domain have good correlation with the grinding-wheel conditions. The grinding wear plot was established to identify the grinding wheel conditions. Using the established experimental set-up, AE signature is captured for the whole cycle of the grinding wheel. AE Signatures are transformed in the wavelet domain and the wavelet coefficients are extracted in the Continuous Wavelet domain and Discrete Wavelet domain. These coefficients carry potential information regarding the condition of the grinding wheel. The mother wavelet chosen in this study for DWT are Haar, Daubechies, Symlets, and Coiflets and for CWT, the Morlet wavelet is used. Using the wavelet coefficients extracted using DWT and CWT, statistical models are built for predicting the condition of the grinding wheel using the J48 and CART algorithm.
In the CWT domain, J48 and CART models trained with Morlet wavelet coefficients are producing better classification accuracy and kappa statistics compared to models trained with wavelet features extracted from the Discrete wavelet domain. The CART complex tree classifier can predict the grinding wheel conditions with a maximum classification accuracy of 97.06 % and kappa value of 0.956. Wavelet analysis is found to be effective in predicting the grinding wheel conditions using J48 and CART decision tree algorithms. The CWT performed better compared to the DWT in classifying the grinding wheel conditions. The data and knowledge gathered in this research will be helpful for establishing an on-line monitoring system. The methodology proposed in this study may be extended to other types of grinding processes such as cylindrical grinding and centreless grinding.

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**Acknowledgments**

This research is supported by ER & IPR, DRDO, ERIP/ER/0803740/M/01/1194.