Time Domain and Frequency Spectrum Analysis of Sound Signal for Drill Wear Detection

Hamed Rafezi, Mehdi Behzad, and Javad Akbari

Abstract—This paper introduces an approach for drill wear detection. Tool failure in machining processes will result in damages to workpiece. In this approach sound signal of drilling operation is recorded and analyzed in both time and frequency domains. Trend of sound signal statistical features are extracted as the drill becomes worn. Sound signal frequency spectrum is calculated using Fast Fourier Transform (FFT) to detect the effect of drill wear on frequency components of signal. In continue Wavelet Packet Decomposition (WPD) is implemented to focus on detected frequency bands. Finally a Feedforward Backpropagation Neural Network (FBNN) is designed and trained based on sound signal features extracted from wavelet packets. The FBNN classifies the tool state into three classes of wear. This approach provides a tool wear detection strategy with capability of online implementation.

Index Terms—Tool condition monitoring, sound, frequency spectrum, wavelet packets.

I. INTRODUCTION

Removing material from workpiece due to contact between tool and workpiece in machining processes, results in changes in tool geometrical properties. These gradual changes are complex phenomena which are known as tool wear. Tool condition has an essential influence on machined surface quality and dimension of manufactured parts also continuing machining operation with a worn or damaged tool will results in damages to workpiece and even the machine tool itself. This problem becomes more important in supplementary machining processes like drilling which the workpiece usually has passed a lot of machining processes and any damage to workpiece at this stage is irreparable and results in high production losses. Today in industry tool changing procedures are based on a conservative tool life estimation which doesn't take into account full life time of tools so avoidable changes will result in time and cost losses [1]. Consequently an effective Tool Condition Monitoring (TCM) is a vital demand in order to develop automated unmanned production.

Tool condition monitoring has been studied by researchers since the late 1980s [2]. However the success of industrial implication of TCM systems is poor [3]. J. Barreiro et al. [4]

used digital images from single point cutting tool to describe tool wear based on image processing methods in turning process. A set of insert flank images was acquired. Several operations were carried out to improve image

appearance. A low pass filter was used to make the background softer and to make the image segmentation easier. C. Aliustoglu et al [1] studied root mean square (RMS), standard deviation and mean values which were obtained from the time domain of vibration signal. Also is mentioned that because of complexity of tool wear process, variation of machining factors such as spindle speed and feed rate will effect the outcome of tool wear detection procedure, so it is vital to consider effect of cutting condition on signal features which are covered in present study. Sidney Ly et al [5] collected vibration signals from accelerometer to develop a TCM system in drilling of 4340M alloy steel. The accelerometer was mounted on the drill spindle housing. Data was transformed into a frequency spectrogram. Then statistical thresholding method or a stack representation of the spectrogram is used in order to normalize the spectrogram and to provide signal features. D.R. Salgado et al [3] developed an approach based on feed motor current and sound signals in turning process. Information of sound signal was extracted using Singular Spectrum Analyses (SSA). The SSA method builds a matrix from the original time series, called the trajectory matrix. In their study, effect of tool wear on eigenvalues of trajectory matrix is inspected. It is concluded that the eigenvalue corresponding to lower frequency range is more affected by ambient noise. Other approaches are available that have inspected limited range of frequency. Like the study done by Raman et al [6] that inspected narrow range of sound frequency between 2.75 and 3.75 KHz.

In present study, sound signal in drilling of Al-7075 alloy is analyzed to detect tool wear in a wide range of 20 to 20000 Hz. Al-7075 is selected as workpiece because need for low weight airframes has led to development of aluminum alloys used as plates, sheets and extrusions. Time domain signal features are extracted and features trend as tool becomes worn is determined. Experiments were repeated with different cutting conditions and tool diameters to study the effect of these parameters on signal features and wear detection. Frequency spectrum of sound signals is calculated and analyzed to study the influence of cutting conditions, tool diameters and tool wear on frequency components of signals. According to frequency spectrum analysis, wavelet packet decomposition is applied. Finally capability of inspected features for drill wear detection is evaluated and most informative features are introduced.

II. SIGNAL ANALYSIS

A. The Discrete Fourier Transform

The most well-known signal analysis method is Fourier analysis, which breaks down a signal into basic sinusoids of different frequencies. Another way to state Fourier analysis

Manuscript received August 30, 2012; September 23, 2012.

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is as a mathematical technique for transforming the signal from a time domain to the frequency domain. For the special case where there is a sampled sequence is given by Equation 1 [7]. Parameters are introduced in Fig. 2.

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-j(2\pi/N)nk} \quad (1)$$

B. Wavelet Packet Analysis

The wavelet packet method is a generalization of wavelet decomposition that provides a richer range of possibilities for signal analysis. In wavelet analysis, a signal is split into an approximation and a detail. The approximation is then itself split into a second-level approximation and detail, and the process is repeated. For n -level decomposition, there are $n+1$ possible ways to decompose or encode the signal, but in wavelet packet analysis, the details as well as the approximations can be split. This yields $2n$ different ways to encode the signal. Approximation part of signal $x(t)$ is generated by Equation 2, where $\phi_{m,n}$ is the wavelet scaling function. 'm' is scale index and 'n' is dilation index [8].

Fig. 1. Time domain signal (a), corresponding Fourier transform (b) [7].

$$S_{m,n} = \int_{-\infty}^{\infty} x(t) \phi_{m,n}(t) dt \quad (2)$$

Detail part of signal $x(t)$ is generated by Equation 3, where $\psi_{m,n}$ is the mother wavelet function.

$$T_{m,n} = \int_{-\infty}^{\infty} x(t) \psi_{m,n}(t) dt \quad (3)$$

III. EXPERIMENTS

Experiments include measurement of sound pressure signal during drilling of aluminum 7075 alloy. Drilling was done on a DAH LIH 1020A vertical CNC machining centre in different cutting conditions (i.e. feed rate and spindle speed) and tool diameters to study the effect of cutting conditions and tool diameter sound signal features. Experiment parameters are given in Table I.

A professional AKG microphone with frequency range of 2- 20000 Hz and a SONY laptop computer were used for sound signal acquisition. The microphone was placed at a fixed distance from cutting area. Experiment setup is shown in Fig. 2. Sound signal analysis was done in MATLAB R2008-a environment.

All experiments started with a new drill and continued until breakage of worn tool. At first, signal features (i.e. root-mean-square, signal peak, mean, variance, standard deviation, skewness and kurtosis) were extracted in time domain. Features trends as tool becomes worn were determined. Then

frequency spectrum of signals was calculated using discrete Fourier transform. Frequency spectrum of sound signals for all experiments were analyzed and compared to study the effect of drilling parameters and tool wear on frequency components of signal. Frequency bands of signal that are affected by tool wear were detected by frequency spectrum analysis. According to detected frequency bands, Wavelet Packet Decomposition (WPD) was implemented to focus on specific frequency bands that were affected by tool wear. In addition WPD was implemented for elimination of environmental noises from sound signal to develop a comprehensive and reliable TCM approach for industrial applications.

Fig. 2. Experiment setup including sensors.

IV. RESULTS AND DISCUSSION

A. Time Domain Analysis of Sound Signal

Signal statistical features including RMS, peak, variance, skewness and kurtosis signal were extracted and analyzed for all experiments with different cutting parameters and tool diameters. Features trend as tool becomes worn was extracted and it was found that just RMS, peak and variance of signal are capable to detect tool wear very well. Figs. 3 shows the trend of sound signal RMS and the effect of federate and spindle speed on sound signal RMS. Fig. 4 that sound signal RMS increases as tool diameter increases.

In this plot 'F' corresponds to feed rate (mm/min) and 'S' corresponds to Spindle speed (rpm). Remarkable result is the direct relationship between sound signal RMS and wear increment. Similar trends for sound signal variance and peak were observed as the drill becomes worn.

Similar incremental trends for variance and peak of sound signal were observed as the drill wear increases.

B. Frequency Spectrum Analysis

In order to analyze sound signal in more depth, frequency spectrum of sound signals for all experiments were calculated. Fig. 5 makes a good comparison between frequency spectrums of signals corresponding to sharp and worn tool. By comparison of frequency spectrum of sound signal correspond to sharp and worn tool in different cutting conditions given in Table I, it is concluded that just frequency components bellow 10 KHz are affected by tool wear and other frequency components are similar for worn and sharp tool. Similar results were obtained in other drilling conditions. This is a guideline to focus on frequency band that are affected by tool wear for feature extraction rather

than whole sound signal. The inspection of specific frequency bands of signal was done by a three-level wavelet packet decomposition. Fig. 6 illustrates three-level wavelet packet decomposition of sound signal generated by the sharp drill.

TABLE I: DRILLING OPERATION PARAMETERS

Parameter	Values
Drill diameters (D)	4, 6, 8 mm
Feed rates (F)	500, 1000 mm/min
Spindle speed (S)	3000, 5000 rpm

Fig. 3. Sound signal RMS for different cutting parameters and tool diameter of 6 mm.

According to frequency spectrum analysis, affected frequency bands by tool wear are detected. These bands are corresponding to packets (3,0), (3,1), (3,2) and (3,3). Extracting signal features from mentioned packets rather than the whole primary signal makes a very better contrast between sharp and worn tool. Fig. 7 illustrates capability of sound signal packet features to increase the contrast between RMS of sound signal for sharp and worn tool.

Fig. 4. Effect of tool diameter on sound signal RMS.

Fig. 5. Frequency spectrum of sound signal: (a) for sharp tool, (b) for worn tool.

Fig. 6. Three-level wavelet packet decomposition of sound pressure signal generated by sharp drill.

Fig. 7. Different percentage of sound signal RMS for sharp and worn tool.

C. Environmental Noise Elimination

An important issue in sound signal analysis is to filter environmental noises. In case of tool condition monitoring, these noises are produced by other machine tools, fans, human voice, etc. In this study, to remove effect of these disturbances on wear detection procedure, sound signal of workshop at place of drilling machine was recorded for 1 minute in 10 different days. Frequency spectrum of workshop sound was calculated. This frequency spectrum showed that all environmental noises of workshop, at place of under study machine have only frequency components below 2 KHz. So packet (3,0) of sound signal is affected by workshop environmental noises. According to frequency spectrum analysis packet (3,1), (3,2) and (3,3) which are affected by tool wear are clear from environmental noises of workshop. So trend of features extracted from these packets provide a reliable relation with tool wear.

Fig. 8. FBNN schematic view.

V. DRILL WEAR STATE CLASSIFICATION

In this section a Feedforward Backpropagation Neural Network (FBNN) is trained and implemented to classify drill wear state in drilling process. Training is done based on

signal features extracted from wavelet packets. The architecture of implemented network is shown in Fig. 8. It has one hidden layer including 8 log-sigmoid neurons and there are 3 log-sigmoid neurons at output layer correspond to three classes of tool wear state. Input attributes of FBNN are given in Table II. The output classes are defined as sharp tool, workable tool and worn tool.

TABLE II: FBNN INPUT ATTRIBUTES

Network inputs		
Sound signal	RMS	Packet (3,1)
		Packet (3,2)
		Packet (3,3)
	Variance	Packet (3,1)
		Packet (3,2)
		Packet (3,3)
	Peak	Packet (3,1)
		Packet (3,2)
		Packet (3,3)
Cutting parameters	Tool diameter	
	Feed rate	
	Spindle speed	

In order to make a precise prediction, sum-squared error is defined as loss function E over the model parameters (weights and biases). The sum-squared error is given by Equation 4 [9]. Where y is the model output and t is the target value. 15 % of dataset was put aside to test the network and it was observed that the network carries out the tool state classification with approximately 90% of accuracy.

$$E = \frac{1}{2} \sum_i (t_i - y_i)^2 \quad (4)$$

VI. CONCLUSION

In this study sound signal of drilling operation was analyzed in both time domain and frequency spectrum to detect the tool wear in drilling operation. A remarkable property of developed approach is implementation of sensor with relatively low expenditure to reduce imposed costs to manufacturer. In addition this approach provides capability of online implementation without process interruption. Experiments were carried out with different cutting

conditions and tool diameters to inspect effect of these parameter on sound signal and the wear detection. Drilling sound signal was recorded and signal statistical features were extracted. Trend of features as tool becomes worn was determined. Sound signal RMS, variance and peak were affected by tool wear with a meaningful trend. In order to analyze signals in more depth, frequency spectrum of signals was calculated using Fast Fourier Transformation to detect the frequency bands which were affected by tool wear. Then the wavelet packet decomposition was implemented to focus on frequency bands that were affected by tool wear. According to frequency spectrum analysis, sound signal frequency bands corresponding to packets (3,1), (3,2) and (3,3) of sound signal have informative features for wear detection. In addition workshop noises have no influence on these frequency bands. Finally based on wavelet packet features, a FBNN was trained to classify tool state in three classes of wear. The FBNN is capable to classify the tool wear state with approximately 90% of accuracy.

REFERENCES

- [1] C. Aliustaoglu, H. M. Ertunc, and H. Ocak, "Tool wear condition monitoring using a sensor fusion model based on fuzzy inference system," *Mechanical Systems and Signal Processing*, 2009, pp. 539–546.
- [2] Z. Kunpeng, W. Y. San, and H. G. Soon, "Wavelet analysis of sensor signals for tool condition monitoring: A review and some new results," *International Journal of Machine Tools and Manufacture*, vol. 49, 2009, pp. 537–553.
- [3] D. R. Salgado and F. J. Alonso, "An approach based on current and sound signals for in-process tool wear monitoring," *International Journal of Machine Tools and Manufacture*, vol. 47, 2007, pp. 2140–2152.
- [4] J. Barreiro, M. Castejon, E. Alegre, and L. K. Hernandez, "Use of descriptors based on moments from digital images for tool wear monitoring," *International Journal of Machine Tools and Manufacture*, vol. 48, 2008, pp. 1005–1013.
- [5] L. Sidney and J. J. Choi, "Drill condition monitoring using ART-1," 1994.
- [6] A. B. Sadat and S. Raman, "Detection of tool flank wears using acoustic signature analysis," *Wears*, vol. 115, no. 3, 1987, pp. 265–272.
- [7] K. Shin and J. K. Hammond, "Fundamentals of signal processing for sound and vibration engineers," *John Wiley and Sons, Inc*, New York, 1994.
- [8] P. S. Addison, "The illustrated wavelet transform handbook," *institute of physics publishing*, London.
- [9] C. M. Bishop, "Neural Networks for Pattern Recognition," *Clarendon Press*, Birmingham, 1995.