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Tool Condition Monitoring using Competitive Neural Network and Hilbert-Huang Transform

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ABSTRACT

One of the major problems in fully automated manufacturing systems is the breakage and deterioration of the tools. Efficient tool condition monitoring systems are required to address such problem. In this study, a new method is proposed for tool condition monitoring for turning operation. The proposed method monitors the condition of the tool flank wear by classifying the tool into any one of the three states; initial wear, medium wear and severe wear. This classifying is done by a trained competitive neural network. The network is trained by using the instantaneous frequencies and amplitudes extracted from the audible emitted tool sound signal by using the new signal processing technique Hilbert-Huang transform. The proposed new method is tested by the audible sound signals collected from a turning machine while machining carbon steel with new, slightly worn and severely worn carbide inserts coated with Aluminum titanium nitride. From the marginal spectrum of Hilbert-Huang Transform analysis it is found that the amplitude of the emitted sound is increasing staidly as the tool flank wear is progressing with time. This correlation between the amplitude of the tool sound and tool flank wear enabled the trained competitive neural network to perform tool wear classification with 80% of accuracy. Hence, the new method can be implemented in tool condition monitoring of turning machines.

Key words: Competitive neural network, empirical mode decomposition, Hilbert-Huang transform, marginal spectrum, tool condition monitoring, tool sound

INTRODUCTION

Efficient tool condition monitoring systems are required to support the fully automated manufacturing systems. According to Byrne *et al.* (1995), monitoring systems are most often used in turning and drilling processes and no monitoring system should be expected to operate with 100% reliability, although failures almost always occur due to human error. Flank wear which occurs on the tool flank as a result of friction between the machined surfaces of the work piece is the most important wear type from the process point of view. Flank wear affects to the great extent, the mechanics of cutting. Cutting forces increase significantly with flank wear (Marinov, 2008). The increased cutting force may cause tool breakage if the amount of flank wear exceeds some critical value (VB>0.5~0.6 mm), therefore the parameter which has to be controlled is the width of flank wear land, VB. It is suggested that the VB for carbide cutting tools should not exceed 0.4 mm (Marinov, 2008; Micheletti, 1976). Tool flank wear need to be monitored because it affects the production significantly (Sick, 2002).

Indirect methods are mostly used in tool condition monitoring systems. In such methods the relationship between tool wear and the process variables (such as vibration, cutting force, temperature, surface roughness, acoustic emission, audible sound etc.) are normally used to identify the amount of tool wear. The combined output of radial force, feed force and AE (RMS value) was utilized to model the tool flank wear in a turning operation. Damodarasamy and Raman (1993) used radial force, feed force and AE (RMS value) together to model tool flank wear system for turning operation. Salgado and Alonso (2007) used feed cutting force, estimated from feed motor current and the information extracted from sound signal to predict the tool flank wear using artificial neural network. Sadettin *et al.* (2007) found that the amplitude of the vibration increases steadily with the increasing tool wear Ming-Chyuan and Kannatey-Asibu (2002) and Alonso and Salgado (2005) managed to monitor the tool flank wear using singular spectrum analysis on audible sound generated from the cutting process. In this research audible sound emitted from tool insert is used for tool wear classification.

The traditional data analysis methods such as Fourier analysis assume the signals are linear and stationary. According to Peng *et al.* (2005), the signal to be processed must be linear and temporarily stationary; otherwise, the resulting Fourier spectrum will make little physical sense. According to Huang *et al.* (1998), the Fourier transform represents the global rather than any local properties of the signal because it employs a convolution integral through which the signal is decomposed in terms of sine and cosine functions covering uniformly the whole data span. Wavelet transform, the time-frequency analysis method, can generate both time and frequency information of a signal simultaneously through mapping one dimensional signal to a two-dimensional time-frequency plane. However, it is also suffering with deficiencies like border distortion and energy leakage that makes the result difficult to interpret (Peng *et al.*, 2001). Hence, new methods are needed to analyze the data from non-linear and non-stationary processes like turning.

Hilbert-Huang Transform (HHT) is considered to have the potential of becoming a perfect method for analyzing non-stationary and nonlinear data (Lisha *et al.*, 2003) which is derived from the principles of Empirical Mode Decomposition (EMD) and the Hilbert Transform. It is a two-step process devised by Huang *et al.* (1998). Firstly, EMD is applied to decompose the given signal into a set of complete and almost orthogonal components called Intrinsic Mode Functions (IMF). Since the IMF is almost mono-component, it can determine all the instantaneous frequencies from a nonlinear and non-stationary signal. Secondly, the local energy of each instantaneous frequency component can be obtained through the Hilbert transform (Peng *et al.*, 2005). Zhang (2006) successfully applied this new signal processing technique in analyzing vibration signals and faults diagnosis of roller bearing. In this research HHT is used to extract features for tool flank wear classification from emitted sound.

Artificial neural network has been a better choice for researchers in tool condition monitoring because of its advantages such as superior learning, noise suppression and parallel computation (Rangwala and Dornfeld, 1990). Rangwala and Dornfeld (1990) used a neural network to integrate information from acoustic emission and force to monitor the occurrence of tool wear in a turning operation. Lin and Ting (1996) successfully trained a neural network, using a cumulative back-propagation algorithm to identify the tool wear conditions based on the thrust force and torque signals while drilling. Choon and Dornfeld (1996) suggested that when the great variety of work piece materials, tool materials and cutting conditions is taken into account a supervised procedure requiring a known value of tool condition for each input of sensor signals from the numerous combinations of machining configurations is far from practical. They also recommended using competitive learning based unsupervised methods. Finally, Sick (2002) in his review of more than a decade of research on-line and indirect tool wear monitoring in turning with artificial neural networks, concluded that it is possible to estimate or to classify certain wear parameters by means of neural networks. He also concluded that despite of more than a decade of intensive scientific research, the development of tool wear monitoring systems is an on-going attempt. In our research, the combination of HHT and competitive neural network has been attempted to classify the flank wear for tool condition monitoring systems.

MATERIALS AND METHODS

The various stages of the proposed method are shown as Fig. 1. The input stage records the emitted sound from the tool as input which is a multi-component signal. Features extraction stage uses EMD to decompose the multi-component sound signal into several mono-component IMFs. This decomposition is needed because the signal consists of tool emitted sound and the various unwanted signals such as sound generated by rotational components and environmental noise. Hilbert Transform (HT) is then applied on each IMFs to extract the local energy in the form of Instantaneous Amplitude (IA) of each Instantaneous Frequency (IF) found in the IMFs. The required IMF corresponding to the emitted tool sound is then selected in the IMF selection stage of feature extraction. The classification stage with competitive neural network uses the RMS Instantaneous Amplitude (IA) and the mean Instantaneous Frequency (IF) to classify the tool into any one of the three states (Initial wear, medium wear and severe wear) which is the output of this tool condition monitoring system. An ICP microphone is used to record the tool emitted sound. A strong correlation between tool wear and the emitted sound is needed for the neural network to classify the tool wear from the emitted sound. This correlation is investigated in this research and it is discussed in the results and discussion section. The selection of required IMF and the classification accuracy of the neural network are also tested in this research.

Hilbert-Huang transform (HHT): It is a new two-step signal processing technique derived by Huang *et al.* (1998) more suitable for analyzing non-stationary and nonlinear data. Firstly, EMD is applied to decompose the given signal into a set of complete and almost orthogonal components called Intrinsic Mode Functions (IMF). Since the IMF is almost mono-component, it can determine all the instantaneous frequencies from a nonlinear and non-stationary signal. Secondly, the local

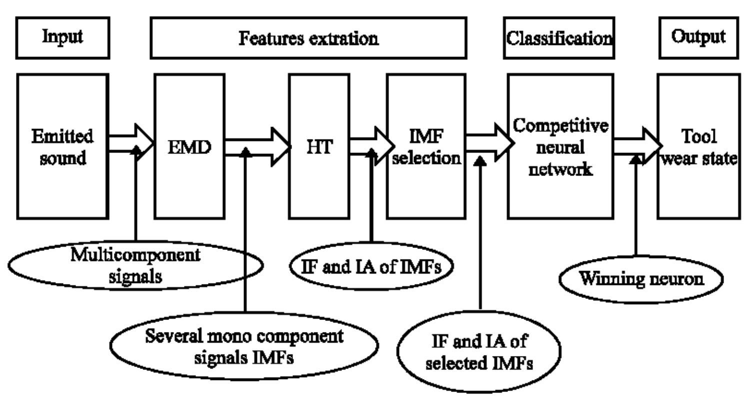

Fig. 1: Block diagram of the proposed tool condition monitoring system

energy of each instantaneous frequency component can be obtained through the Hilbert transform (Peng *et al.*, 2005). If the inspected signal is multi-component within the defined time frame, the result of the instantaneous frequency will be distorted (Rilling *et al.*, 2003). Unfortunately, in almost all of the practical applications, the inspected signals are hardly mono-component but multi-component. Therefore to make the instantaneous frequency applicable, the key is the ability to decompose the signal into some individual mono-component signals. The Empirical Mode Decomposition provides such decomposition ability.

Empirical mode decomposition (EMD): The data, depending on its complexity, may have many different coexisting modes of oscillation at the same time. Each of these oscillatory modes is represented by an Intrinsic Mode Function (IMF) with the following definitions (Huang *et al.*, 1998):

- In the whole data set, the number of extreme and the number of zero-crossings must either equal or differ at most by one
- At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero

To extract the IMF from a given data set, the sifting process is implemented as follows (Rilling *et al.*, 2003). First, identify all the local maxima and then connect all of the local maxima by a cubic spline line as the upper envelope. Then, repeat the procedure for the local minima to produce the lower envelope. The upper and lower envelopes should cover all the data between them. Their mean is designated $m_1(t)$ and the difference between the data and $m_1(t)$ is $h_1(t)$, i.e.:

$$x(t)-m_1(t) = h_1(t) \tag{1}$$

The sifting process has to be repeated as many times as it is required to reduce the extracted signal to an IMF. In the subsequent sifting process steps $h_1(t)$ is treated as the data; then:

$$h_1(t)-m_{11}(t) = h_{11}(t) \tag{2}$$

where, $m_{11}(t)$ is the mean of the upper and lower envelops of $h_1(t)$. This process can be repeated up to k times; $h_{1k}(t)$ is then given by:

$$h1_{(k-1)}(t)-m_{1k}(t) = h_{1k}(t) \tag{3}$$

After each processing step, checking must be done on whether the number of zero crossings equals the number of extrema. The resulting time series is the first IMF and then it is designated as $c_1(t) = h_{1k}(t)$. The first IMF component from the data contains the highest oscillation frequencies found in the original data x(t).

This first IMF is subtracted from the original data and this difference, is called a residue $r_1(t)$ by:

$$x(t)-c_1(t) = r_1(t) \tag{4}$$

The residue $r_1(t)$ is taken as if it was the original data and we apply to it again the sifting process. The process of finding more intrinsic modes $c_i(t)$ continues until the last mode is found. The final residue will be a constant or a monotonic function:

$$x(t) = \sum_{j=1}^{n} c_j(t) + r_n(t) \tag{5}$$

Thus, one achieves a decomposition of the data into n-empirical IMF modes, plus a residue, $r_n(t)$, which can be either the mean trend or a constant.

Hilbert transform: The physically meaningful way to describe the system is in terms of the instantaneous frequency, which will reveal the intra wave frequency modulations (Huang *et al.*, 1998). The easiest way to extract or compute the instantaneous frequency of a mono-component signal is by using Hilbert transform. For an arbitrary signal or time series x(t), its Hilbert transform y(t) is defined as:

$$y(t) = \frac{P}{\pi} \int_{-\infty}^{+\infty} \frac{x(\tau)}{t-\tau} d\tau \tag{6}$$

where, P is the Cauchy principal value of the singular transform. This function exists for all functions of class of Lebesgue spaces (Titchmarsh, 1948) or L^P. Equation 6 shows that the Hilbert transform is defined as the convolution of the signal x(t) with 1/t. Therefore, the Hilbert transform is capable of identifying the local properties of x(t). Coupling the x(t) and y(t), we can have the analytic signal z(t) of x(t), as:

$$z(t) = x(t)+iy(t) = a(t)e^{i\varphi(t)} \tag{7}$$

$$a(t) = [x_2(t)+y^2(t)]^{1/2},\ \varphi(t) = \arctan(y(t)/x(t)) \tag{8}$$

where, a(t) is the instantaneous amplitude of x(t), which can reflect how the energy of the x(t) varies with time and the $\phi(t)$ is the instantaneous phase of x(t). The controversial instantaneous frequency $\omega(t)$ is defined as the time derivative of the instantaneous phase $\phi(t)$, as follows:

$$\omega(t) = d\varphi(t)/d(t) \tag{9}$$

Because the instantaneous frequency is defined through differentiation rather than integration it appears to be local and can describe intra-wave frequency modulation. Therefore, Eq. 9 is useful in extracting instantaneous frequencies from any non-stationary signals. However, Eq. 9 is only valid in obtaining the instantaneous frequency of a signal in a given time frame if the signal is mono-component within the time frame.

Marginal spectrum: According to Eq. 7 it is possible to represent the amplitude and the instantaneous frequency, in a three-dimensional plot, in which the amplitude is the height in the time-frequency plane. This time-frequency distribution is designated as the Hilbert spectrum $H(\omega,t)$:

$$H(\omega, t) = \mathrm{Re}\sum_{i=1}^{n} a_i(t)e^{j\int w_i(t)dt} \tag{10}$$

With the Hilbert spectrum defined, the marginal spectrum, h(ω), can be defined as:

$$h(\omega) = \int_0^T H(\omega, t)dt \tag{11}$$

where, T is the total data length.

The Hilbert spectrum offers a measure of amplitude contribution from each frequency and time, while the marginal spectrum offers a measure of the total amplitude contribution from each frequency (Huang *et al.*, 1998; Zhang, 2006). Therefore, local marginal spectrum of each IMF component is given as:

$$h_i(\omega) = \int_0^T H_i(\omega, t)dt \tag{12}$$

The local marginal $h_i(\omega)$ spectrum offers a measure of the total amplitude contribution from the frequency. According to marginal spectrum, the characteristic amplitude of the tool flank wear can be easily recognized and thereby the condition of the tool wear can easily be determined.

Competitive neural network: The proposed competitive neural network (Fig. 2) consists of two neurons (IN_1 and IN_2) in the input unit and three neurons (ON_1, ON_2 and ON_3) in the output unit. The RMS Instantaneous Amplitude (IA) and the mean Instantaneous Frequency (IF) of the selected IMF are given as input.

The three output neurons are representing the three different states of the tool wear, fresh, slightly worn and severely worn. Each input neuron is connected to every output neuron thus forming the weight matrix of 3 rows and 2 columns. The weights are initialized to the centers of the input ranges with the function midpoint. Because the input range is 0.03 to 0.21 for amplitude and 280 to 510 for frequency (obtained from HHT analysis), all the three output neurons' weight are initialized to 0.12 and 395.

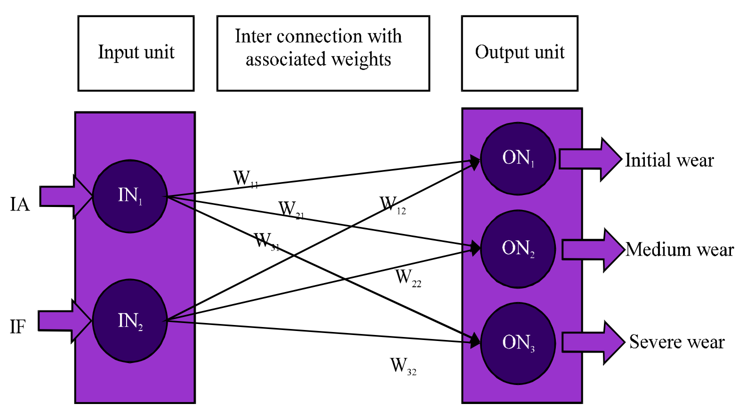

Fig. 2: The proposed competitive neural network

Winner takes all unsupervised learning algorithm the Kohonen Learning Rule (learn from MATLAB) is used to update the weights of the winning neuron. Supposing that the ith neuron wins, the elements of the ith row of the input weight matrix are adjusted as shown below (Kohonen, 1984):

$$W_i\,new = W_i\,old+\eta(X-W_i\,old) \tag{13}$$

where, W_i new represents the updated weights of the winning neuron i and W_i old represents the existing weights of the winning neuron. The constant η represents the learning rate for the weight adjustments and 0.5 is used in this experiment. It represents the fraction of the distance that the winning neuron will move toward the input data vector. X represents the input vector consists of IA and IF.

Experimental set-up: The photograph of actual excremental setup is shown as Fig. 3. A PCB 130D20 microphone is mounted on the side of the coolant pipe and facing towards the tool tip to capture the emitted sound (Kopac and Sali, 2001). The microphone is connected to the computer through a specially designed signal conditioner. GoldWave software is used to record the captured sound with sampling frequency set to 44100 Hz.

A series of machining experiments were conducted on a Turning machine (KNUTH Basic 180 V) with Carbide insert coated with Aluminum titanium nitride and carbon steel work piece with a diameter of 25 mm. First, the free running sound for the spindle rotational speed of 570 rev min^{-1} was recorded, without the machining operation. Keeping the spindle rotational speed at 570 rev min^{-1}, the sound emitted due to machining with a new tool was recorded for the depth of

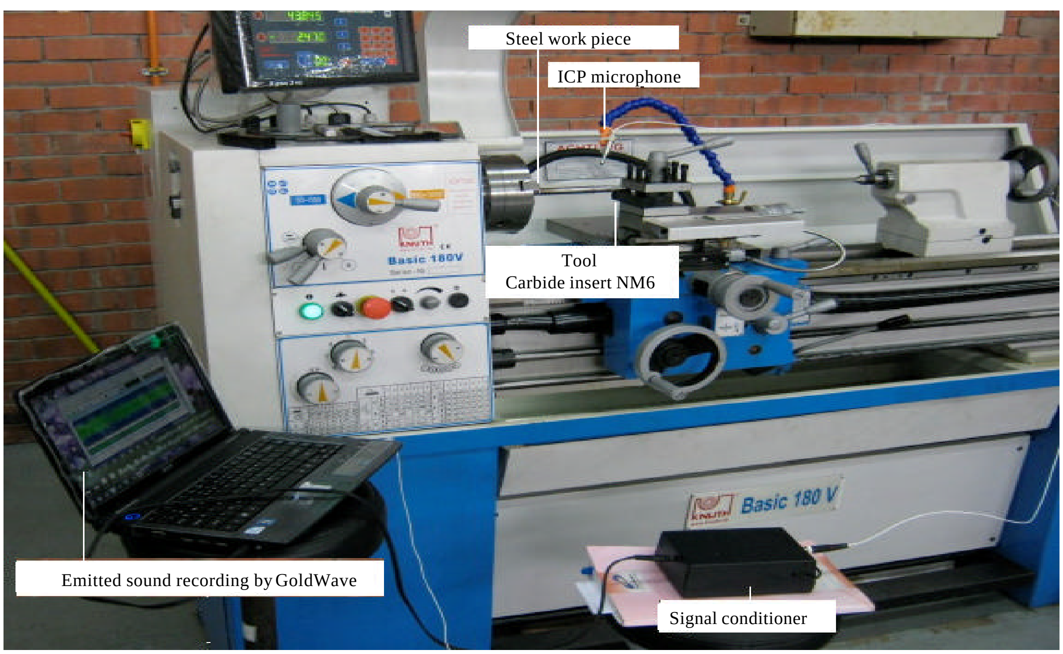

Fig. 3: The photograph of actual experimental set-up

cut of 1 mm. This recording process was repeated separately for slightly worn tool with 0.2 mm flank wear and severely worn tool with 0.4 mm flank wear (Altin *et al*., 2007). A constant feed rate of 0.5 mm rotation^{-1} was maintained throughout the experiment. The 10 sec long sound signal is split into 10 one second sound signals for the subsequent signal processing using HHT. Each one second signal contains 44100 sampling data. The MATLAB wavread function was used to digitize the sound signals.

RESULTS AND DISCUSSION

The results obtained in feature extraction using HHT and the tool wear classifications by neural network are discussed separately in this section.

Feature extraction using HHT: A sample of the recorded multi-component sound signal of severely worn tool is shown in Fig. 4a. It contains various components such as sound emitted from machine rotational parts and the much needed sound emitted due to the contact between the tool flank face and the surface of the work piece. In addition to these components, it also contains the harmonics of the fundamental signals of this kind. The result of EMD applied on the sound signal of severely worn tool is shown in the form of 14 IMFs and the residue in Fig. 4b where each IMF is a mono-component signal.

The instantaneous frequencies and amplitudes were then obtained by applying Hilbert transform on the IMFs. Average amplitude of each IMF for free run, new tool, slightly and severely worn tool sound signals were calculated and line graphs were generated to compare these amplitude values Fig. 5. From Fig. 5 it is very clear that IMF 5 to IMF 7 are representing the sound signal and its harmonics emitted due to the contact of the tool flank face with the surface of the

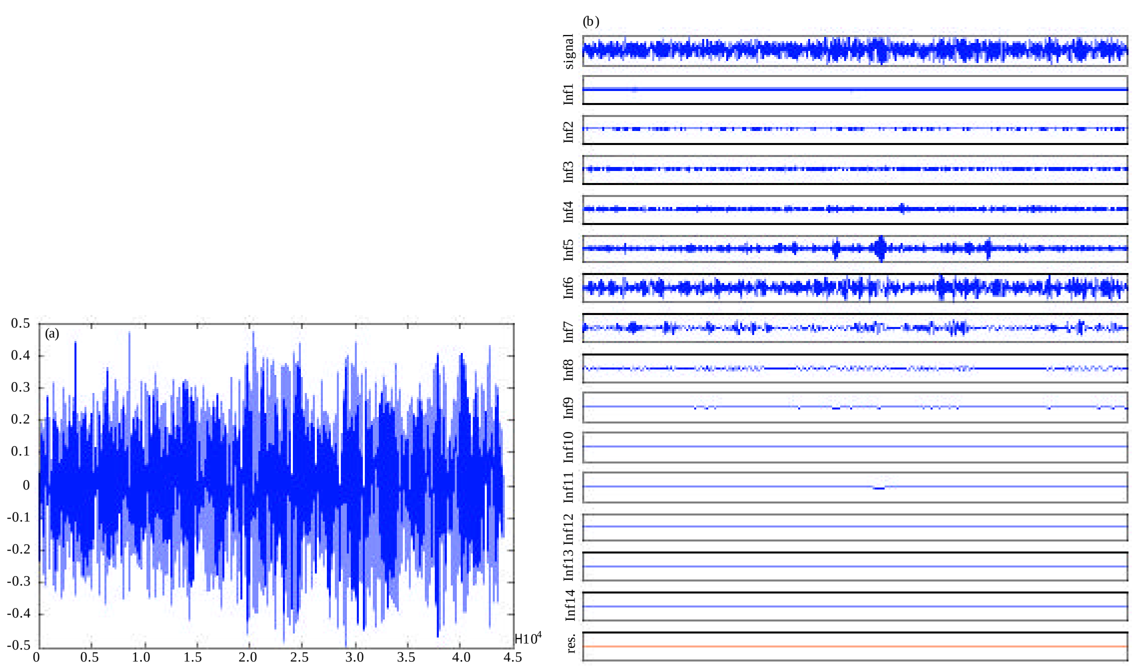

Fig. 4(a-b): The original multi-component sound signal of (a) Worn tool and its (b) Empirical mode decomposition, imf: Intrinsic mode function

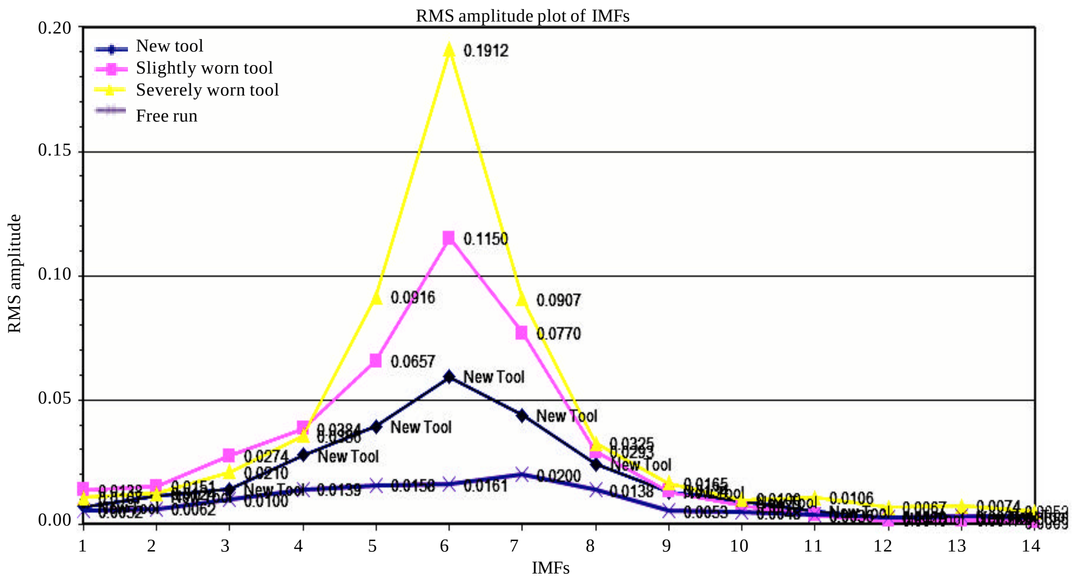

Fig. 5: Comparison of the RMS amplitude found in the IMFs of free run, new tool, slightly and severely worn tool sound signals

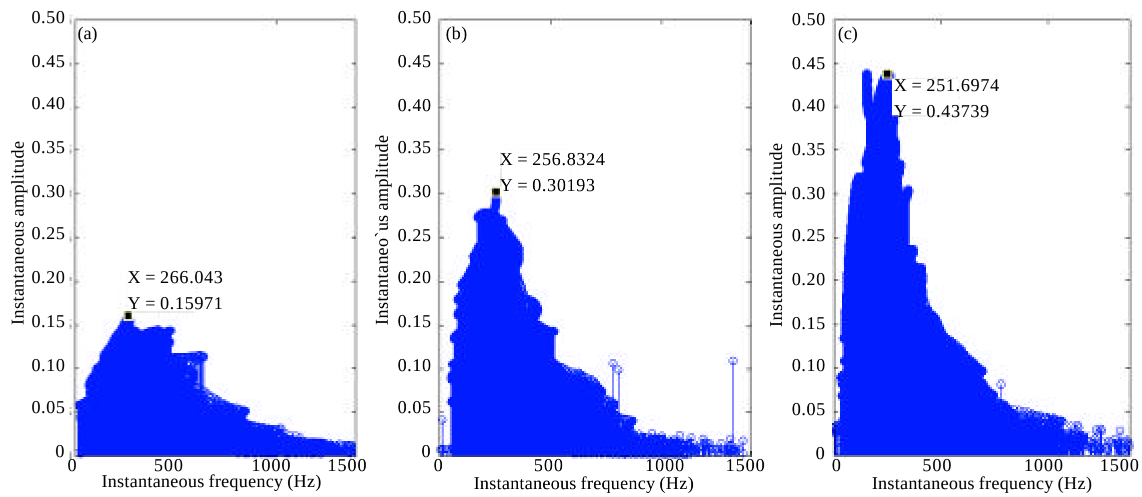

Fig. 6(a-c): Marginal spectrum constructed using IMF 6 of tool sound with (a) Initial, (b) Medium and (c) Severe wear

work piece. This is because the amplitude of these IMFs are different from the amplitude of IMFs corresponding to free run. Out of these three IMFs, more energy in the form of amplitude is found in IMF 6; hence it is appropriate to perform further marginal spectral analysis on IMF 6. The marginal spectrum of IMF 6 for new, slightly and severely worn tool sound signals were obtained as shown in Fig. 6. The maximum amplitude of sound emitted with the new, slightly and severely worn tool bit insert is measured as 0.15971, 0.30193 and 0.43739 are the maximum amplitude of sound emitted with the new, slightly and severely worn tool bit insert. From Table 1 it is found that the sound pressure amplitude of tool bit is increasing with the progress of tool flank wear. These findings show that the amplitude of emitted tool sound is increasing staidly with the progress of tool flank wear.

Tool wear classification by neural network: The data set for training and testing the neural network was prepared with 30 samples taking 10 each from new, slightly worn and severely worn tool sound. Each sample is a vector consisting of RMS value of Instantaneous Amplitudes (IA) and the mean value of Instantaneous Frequencies (IF) of the selected 6th IMF of one second sound signal. The weights of the three output neurons before and after training are shown in Table 2. From Table 2 it is observed that output neuron ON_1 represents the initial wear state of the tool because their weights are closer to the IA and IF of new tool sound. This neuron will fire whenever a sound signal from new tool is input to this network. Similarly ON_2 and ON_3 represent the medium wear and severe wear states of the tool, respectively. This can be clearly viewed from the graph (Fig. 7) plotted with the training data and the weights of the three trained output neurons.

Leave-one-out cross validation technique was used for testing the performance of the competitive neural network. According to this technique for a dataset with N examples, N

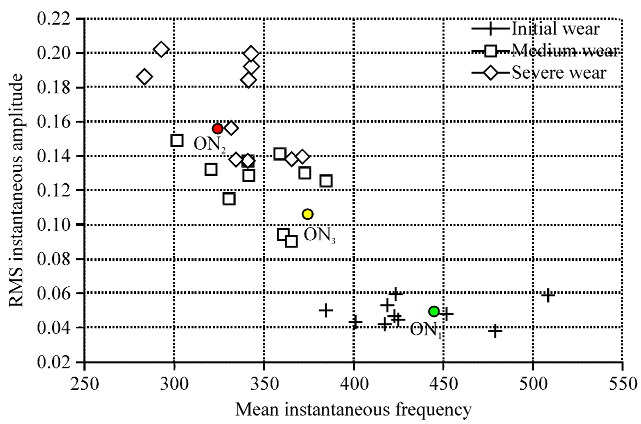

Fig. 7: Tool flank wear classification, ON_1: Weights of the neuron representing initial wear state, ON_2: Weights of the neuron representing severe wear state, ON_3: Weights of the neuron representing medium wear state

Table 1: Amplitude of the sound and the tool wear

		Tool condition	
	New	Slightly worn (0.2 mm flank wear)	Severely worn (0.4 mm flank wear)
Sound pressure amplitude from marginal spectrum	0.15971	0.30193	0.43739

Table 2: Weights of the three output neurons before and after training

	Weights before training		Weights after training	
Output neurons	Amplitude	Frequency	Amplitude	Frequency
ON_1	0.12	395	0.0495	445.26
ON_2	0.12	395	0.1558	324.99
ON_3	0.12	395	0.1058	374.62

experiments need to be performed and for each experiment N-1 examples should be used for training and the remaining example for testing. A total of 30 experiments were conducted and for each experiment 29 samples were used for training and the remaining sample for testing. As usual the true error is estimated as the average error rate on test samples using the following formula:

$$E = \frac{1}{N}\sum_{i=1}^{N} E_i \quad (14)$$

Out of the 30 tests, the trained network failed to classify the input correctly only six times. Hence the rate of error estimated using Eq. 14 in this network is 0.2. In other words the success rate or the percentage of success is 0.8 or 80%, respectively.

CONCLUSION

In this study, a new method is proposed for tool condition monitoring system which includes a competitive neural network with HHT as feature extractor. The correlation between the amplitude of emitted tool sound signal and the growth of tool flank wear made the competitive neural network to classify the state of the tool insert with 80% of accuracy. The correlation was investigated while turning carbon steel and it is found that the amplitude of emitted tool sound signal is increasing staidly with the growth of tool flank wear. Hence the proposed new method can be confidently applied in tool condition monitoring systems for tool flank wear classification.

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