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Discrete wavelet transforms analysis of vibration signals for correlating tool wear in diamond turning of additive manufactured Ti-6Al-4V alloy

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Abstract

Ultra-precision machining (UPM) of Ti-6Al-4V alloy is widely regarded as a challenging material processing due to excessive tool wear and chemical reactivity of the tool and workpiece. Tool wear has a significant influence on the surface quality and also causes damage to the substrate. Therefore, it is critical to consider the tool condition during diamond turning, especially as precision machining moves towards intelligent systems. Consequently, there is a need for effective ways for in-process tool wear monitoring in UPM. This study aims to monitor the diamond tool wear using time-frequency-based wavelet analysis on vibrational signals acquired during the machining of Additively Manufactured (AM) Ti6Al4V alloy. The analysis employed Daubechies wavelet (db4, level 8) to establish a correlation between the Standard Deviation (SD) of the magnitude in the decomposed vibrational signal obtained from both the fresh and used tools. The analysis revealed that at a feed rate of 1 mm/min, the change in SD is 32.3% whereas at a feed rate of 5 mm/min, the change in SD is 8.4 %. Furthermore, the flank wear and microfractures are observed using a scanning electron microscope on the respective flank and rake face of the diamond tool.

Keywords: Tool wear; Vibration signals; ultra-precision machining; wavelet analysis; Additive manufactured Ti-6Al-4V alloy

1 Introduction

With the emerging trends in the area of manufacturing, it has become important to enhance the efficiency of the process and minimize tool wear [1]. The shift of the industries in the area of UPM has clearly shown the need for effective ways of monitoring machining anomalies [2] and tool wear [3]. UPM is observed to be sensitive to minute change and the tool wear affects the quality of parts and impacts production efficiency and part yield [4]. The need for the accurate quantification of the tool condition and to offer autonomous decisions on tool life has been increasingly important. Shi et al. [5] proposed the tool condition monitoring in UPM using multiple-feature from the vibrational signal, suggesting that traditional ways of time-domain signal processing cannot be used for diamond turning. It was also specified from the earlier research, tool signature of the diamond tool in particular nose radii is paramount important in UPM [6]. This is due to the fact that in UPM, chip thickness ratio varies instantly and leads to conditions of regenerative chatter [7]. The detection of tool wear through time domain and frequency domain signal processing is often challenging due to complex spatiotemporal patterns observed in sensor signals. On the other hand, titanium alloy has attracted many researchers due to its unique applications, excellent resistance to corrosion and strength-to-weight ratio [8, 9]. Yip and Sandy explore the ductile to brittle transition during diamond turning of titanium alloy [10]. Selective Laser Melting (SLM) is emerged as dominant metal AM technology, due to its unique advantage of unparallel design freedom with minimum surface defects [11, 12]. One notable advantage of this AM technique is its ability to directly fabricate intricate lenses or mirrors by customizing the material according to specific requirements [13-15]. Akhil et al. demonstrated selective laser melting based additive manufacturing surface characteristics using the analysis of surface images[16]. However, AM Ti-6Al-4V ELI alloy is often treated as difficult to machine due to tool wear and generally requires an appropriate selection of process parameters [17]. Ma et al. explored the influence of the tool quality on machining of AM titanium alloy and powder metallurgy titanium alloy and found that AM titanium limits the lifetime of drill [18]. Colafemina et al.[19] investigated the machinability of pure- titanium and Ti-6Al-4V suggesting ultra-precision diamond turning is a viable option for the finish of Ti-alloy and Ti-6Al-4V alloy.

Moreover, if the diamond tool tip degradation is not detected, it results in high cost and unacceptable surface roughness [20, 21]. Uekita and Takaya [22] examined the influence of the vibrational signal and presented an energy-based chatter criteria capable of preventing tool failure and offering a comprehensive tool status. Mohanraj et al. [23] also developed a condition-based tool wear monitoring using the wavelet feature and holder's exponent with machine learning and found that this wavelet coefficient based analysis showcased better accuracies in comparison with the traditional feature extraction techniques. Sawangsri & Cheng [24] explored innovative wavelet analysis to correlate the tool wear during UPM of titanium, silicon and aluminium alloy. Daubechies wavelet (dbNs) at levels 1-4 is used in this analysis; the results specify that the standard deviation of the cutting force signal is highly correlated to the tool wear in diamond turning. There is a lot of interest growing in the development of tool condition monitoring, tool wear monitoring, Table 1. shows the results of the previously published studies in the area of precision machining.

Table 1: Compression of various tool wear analysis in ultra-precision machining

Author & Year	Workpiece material	Tool material	Findings
Wang et al. (2015) [25]	Single-crystal silicon	Diamond tool	Cutting forces and radial forces analysed using db3, level4 found the correlation with tool wear.
Sawangsri & Cheng (2016) [24]	Aluminium (AA6082-T6), silicon and titanium	Diamond tool	dbN at levels 1-4 is used in this analysis; the results specify that the standard deviation of the cutting force signal is highly correlated to the tool wear in diamond turning
Shi et al. (2018) [5]	Aluminium alloy	Diamond tool	Tool condition monitoring was carried out using multi-feature spaced based deep learning. Parallel learning of using various features (time domain, frequency domain and wavelet domain)

			obtained from vibrational signals are used for classification of tool wear with 93.2% accuracy.
Huang et al. (2021) [26]	stainless steel (HRC52)	tungsten carbide	Tool wear monitoring using vibrational signal based on short-time fourier transform (STFT) and deep convolutional neural networks, the mean average error around 1.3 ±0.372 μm.
Huang & Lu (2023) [27]	ISO TC 120 (SK2 steel)	tungsten carbide	Acoustic emission (AE) and vibration signals were analysed using time domain based and the tool wear is monitored based on wavelet coefficients in three different tool paths. Suggested that frequency domain features are highly correlated to tool wear in precision milling.

Although the earlier research attempted to correlate the tool wear with the signal acquired in ultra-precision machining, these papers lack to provide deeper insights about the tool wear in relation to the feed rates during the diamond turning of AM Ti-6Al-4V alloy. Consequently, an attempt is made in this paper to use the vibrational signal and discrete wavelet transform to monitor the tool wear during machining of AM Ti6Al4V. Also, the variations in the tool wear under various feed rates in fresh and used tools are examined. Further, approximation coefficient standard deviations analysis results are discussed in detail in further sections. Also, Scanning Electron Microscopy (SEM) image analysis was carried out to evaluate the tool wear.

2 Wavelet transforms analysis method

The Wavelet Transform (WT) has been developed for analyzing the nonlinear signals by transforming time domain to the time-frequency domain using window function. This transformation involves the scaling (dilation & contraction) and shifting (translation) of a prototype function known as the mother wavelet. The main distinction between these wavelet functions and complex sinusoids employed in the Fourier transform is that unlike sinusoids, which last for infinity, wavelets have finite duration. Additionally, the sinusoid is uniform and predictable whereas the wavelets are irregular and asymmetric. WT are further classified into two types namely a) Continuous Wavelet Transform (CWT) b) Discrete Wavelet Transform (DWT). CWT is a valuable technique for analyzing non-stationary signals that enable the temporal location of components in the frequency domain. However, CWT suffers from low analytical computational efficiency, which limits its practicality for offline applications. For real-time signal processing, DWT and wavelet packet transform are commonly used in wavelet analysis. DWT is an effective way of analyzing the signals with abrupt changes with quick responses [28]. For example, Rabi et al.[29] detected the abrupt changes in the signals corresponding to defects in friction stir welding using DWT, further suggesting the increase in kurtosis value helps to predict the defect zone..

This method decomposes the signal into a set of mutually orthogonal wavelets using low-pass and high-pass filters. The approximation and detailed coefficients are obtained through this decomposition as described in Equation (1) below, where DWT can be expressed in the form suggested by Zhu et al. [30].

$$f(x) = \sum_k a_{j0,k} \ \emptyset_{j0,k}(x) + \sum_{j=j_0}^{\infty} \sum_k d_{j,k} \ \Psi_{j,k}(x) \qquad (1)$$

Where $a_{j0,k}$ is approximation coefficient and $d_{j,k}$ is detailed coefficient. Coefficients obtained from passing the signal through low-pass (L(k)) and high (H(k)) filters. The relationship between low-pass and high-pass filters and their corresponding scaling (Ø) and wavelet function (ψ) is further described by Equations (2) and (3) below Zhu et al. [30].

$$Ø_{(x)} = \sqrt{2}\sum_{K=0}^{L-1} L(k)Ø_{(2x-k)} \tag{2}$$

$$\Psi_{j,k}(x) = \sqrt{2}\sum_{K=2-L}^{1} H(k)Ø_{(2x-k)} \tag{3}$$

There are various mother wavelet families that are in used in manufacturing to extract meaningful information, as illustrated in Fig. 1(a-c), there are a series of subclasses (e.g., *dB2* and *dB4*) differ in terms of the degree of their coefficients and iterations. Among these, daubechies wavelets are quite popular for the detection of abrupt changes in diamond turning due to computational efficiency and non-redundancy in the decomposition [25,24]. Therefore, in this study the *dB4* mother wavelet is used to analyze the tool wear in diamond turning, where the raw vibrations signals are moved into a transformed space by using the wavelet transformations.

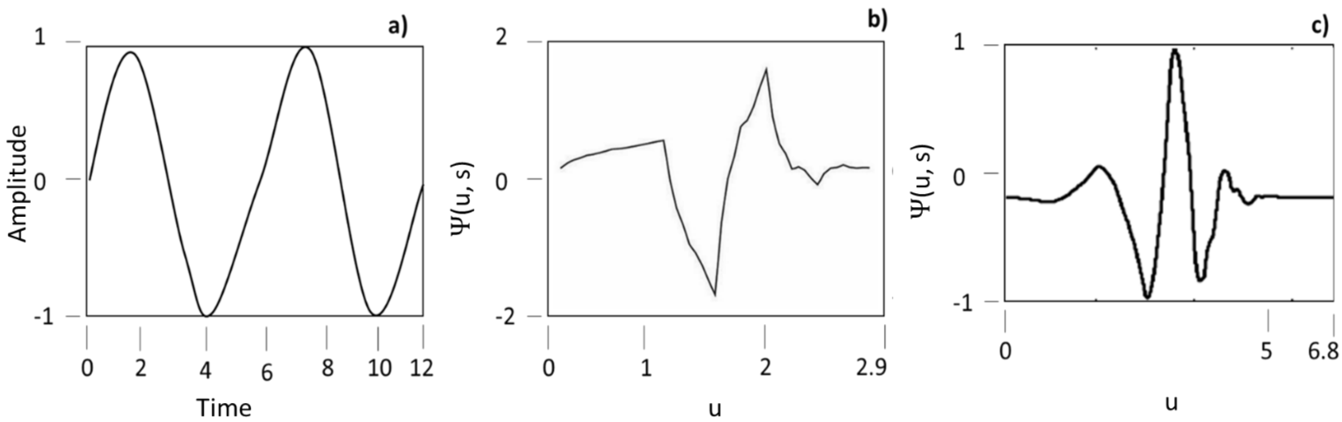


Figure 1. Difference between Sinusoidal and Wavelet a) Sinusoidal wavelet b) *dB2* wavelet and c) *dB4* wavelet (Where ψ is function of wavelet, u is scale or dilation parameter of the wavelet)

3 Experimental study

For the experiments conducted in this study AM Ti-6Al-4V samples are used. The properties used for additive manufacturing and other post-processing are as specified in the Manjunath et al. [31] are used for preparation of the Ti-6Al-4V disks. The respective surface morphology of additively manufactured Ti-6Al-4V alloy at different magnification of SEM at 45X and 90X is given in Fig 2. The surface is dominated by metal melt traces, irregular impurities and bonded powder with different sizes, this is majorly due to many factors including high temperatures, high cooling rates and vapor pressure, which are inherent in the additive manufacturing process.

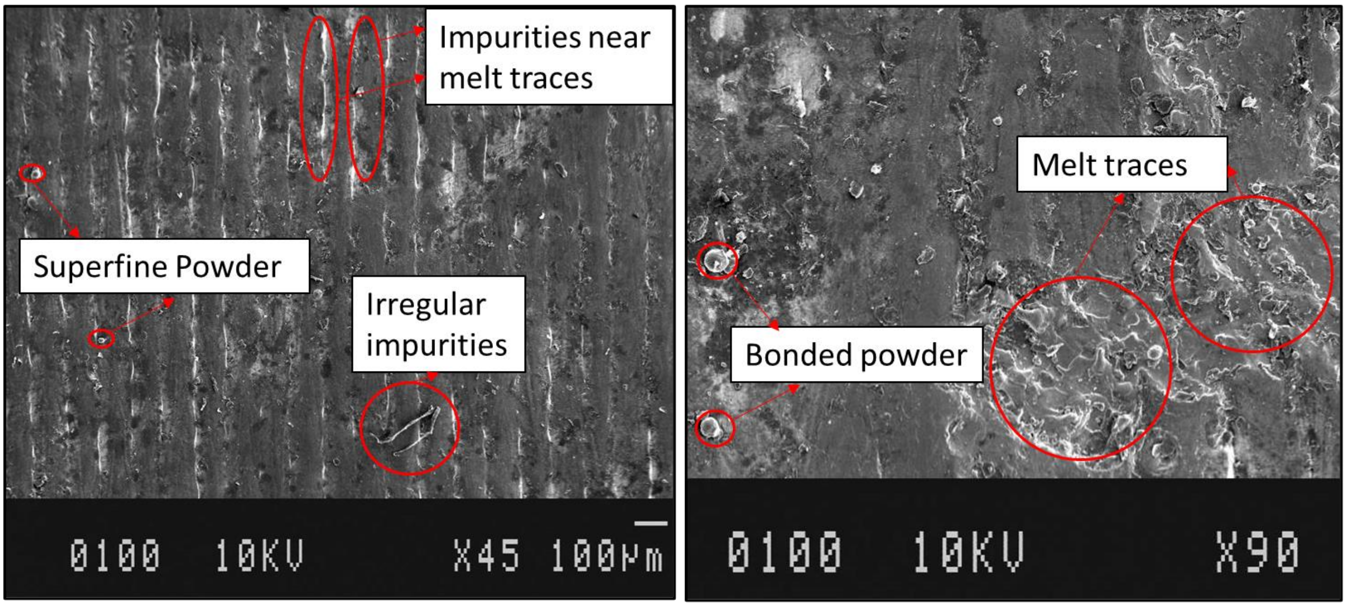


Figure 2. Surface morphology of as built SLM Ti-6Al-4V alloy a) 45X magnification b) 90X magnification

A single-point diamond turning machine (Nanoform 200) is used to perform the diamond turning experiments. The machined workpieces of 25 mm in diameter and 10 mm in thickness are mounted onto the machine using an aluminium fixture. Diamond tool with a 1.5 mm nose radius and 0° rake angle is used for the machining. Each machining trial involves a single pass, and the experimental turning is carried out at feed rates of 1, 5, and 10 mm/min. B&J single-axis accelerometer 4533-B is used for the collection of the vibrational signal. 4533-B is a commonly used IEPE (Integrated Electronic Piezo-Electric) sensor used for a wide range of vibrational experiments. The system was connected with the Dewesoft data acquisition card. The sensor is connected to the Dewesoft data acquisition card, while the sampling frequency is set at 10 kHz.

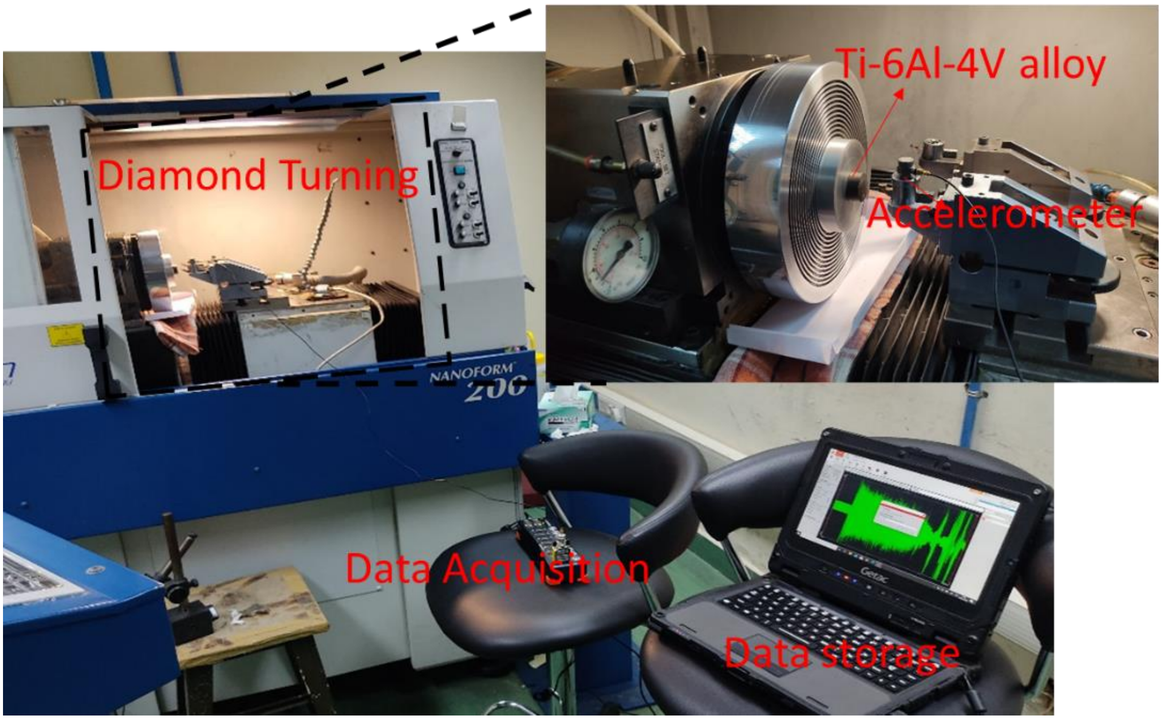
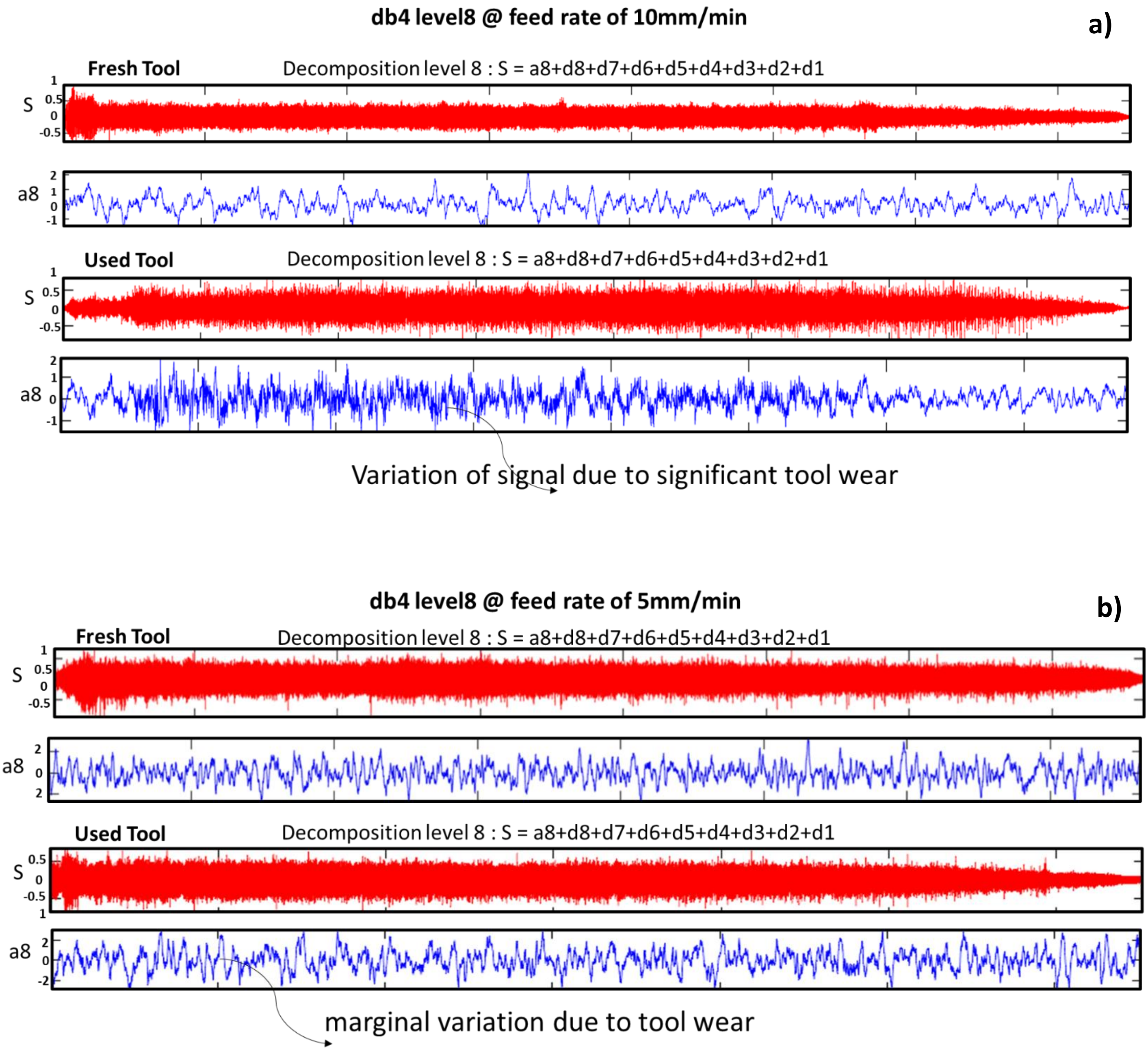


Figure 3. Experimental Setup

The experimental setup for the collection of the vibrational signal is shown in Fig. 2. In this study, MATLAB programming is employed to analyze the behavior of the dB4 wavelet with level 8 decomposition and 1D wavelet decomposition. These methods enable, wavelet decomposition of the signals at N-specified levels, with the wavelet decomposition tree providing the approximated signal for each level. This decomposition aids in obtaining lower-resolution components of the signals.

4 Results and discussion

Figure 4 illustrates the vibration signals obtained for both the fresh tool and the used tool. The time series signal is transformed into a wavelet domain and the respective variation in signal is noted. The presence of abrupt variations in the signals indicates tool wear and the standard deviation of the signals is measured accordingly. By monitoring the vibrational patterns of the signal in the fresh tool and used tools, it can be clearly seen at feed rate 1mm/min and 10mm/min tool wear is very significant. Table 1 specifies the change in the standard deviation of the vibrational signal with respect to variations in feed rates. The approximation coefficient (a8) has shown the clear variation in the signal specifying the mother wavelet is suitable for analyzing and monitoring of tool wear in diamond turning.



db4 level8 @ feed rate of 10mm/min
a)
Fresh Tool
Decomposition level 8 : S = a8+d8+d7+d6+d5+d4+d3+d2+d1
Used Tool
Decomposition level 8 : S = a8+d8+d7+d6+d5+d4+d3+d2+d1
Variation of signal due to significant tool wear
db4 level8 @ feed rate of 5mm/min
b)
Fresh Tool
Decomposition level 8 : S = a8+d8+d7+d6+d5+d4+d3+d2+d1
Used Tool
Decomposition level 8 : S = a8+d8+d7+d6+d5+d4+d3+d2+d1
marginal variation due to tool wear

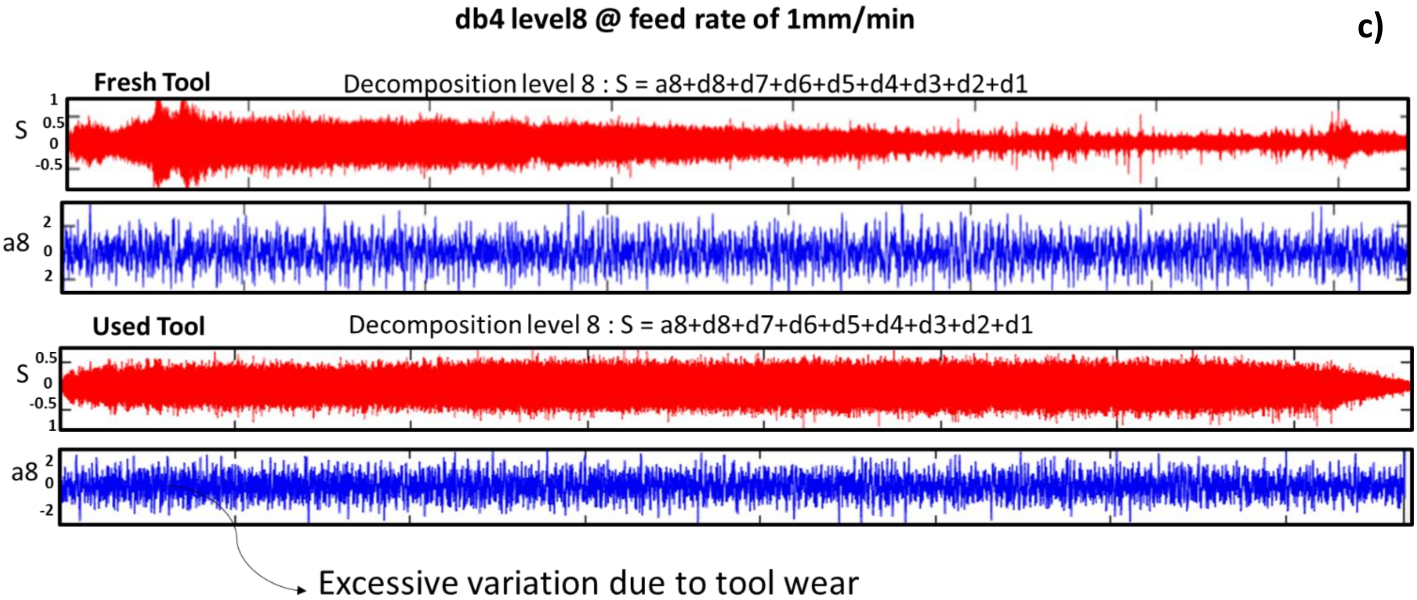


Figure 4. Results of variation in tool wear with the change in feed rates a) 10 mm/min b) 5 mm/min and c) 1 mm/min

Table 2: Variation the standard deviation at various feed rates

	Standard deviation		
Feed rate	Fresh tool	Used tool	% Change
10 mm/min	0.111	0.140	21.1 %
5 mm/min	0.114	0.124	8.4 %
1 mm/min	0.072	0.106	32.3 %

From Fig. 4 (a-c) the decomposed vibrational signals were obtained with the fresh tool and used tools. Further, only marginal wear is seen at 5mm/min (see Fig 4 (b)) whereas more excessive wear is seen at 1mm/min as shown in Fig 4(c). It can be seen from Table.2 the change in standard deviation in the decomposed signal is most at the feed rate of 1 mm/min and it can be seen the change is near 32.3%. whereas the change during the 10 mm/min feed was 21.1%, and the abrupt changes showcase the tool wear. The variation is minimum at 8.4% during the 5 mm/min feed rate. The results show an increase in the magnitude of the standard deviation with an increase in cutting time. In order to gain further insight into the phenomenon, SEM images of the workpieces at different feed rates are studied. Fig. 5 (a-c) shows the SEM images of diamond-turned samples Ti-6Al-4V alloy at 90X magnification. At a feed rate of 10 mm/min grooves with irregular shapes are clearly visible. This formation is primarily attributed to the tool-chip interaction and higher magnitude of the cutting force experienced by the tool.

On the other hand, only minimal groove marks along with small pitting are observed on the machined substrate at 5 mm/min. In contrast, when the feed rate is reduced to 1 mm/min, deep groove marks along with serious pitting is evident on the surface, indicating significant tool wear. This is largely attributed to the lower feed rates, which leads to higher rate of heat generation and chip adhesion.

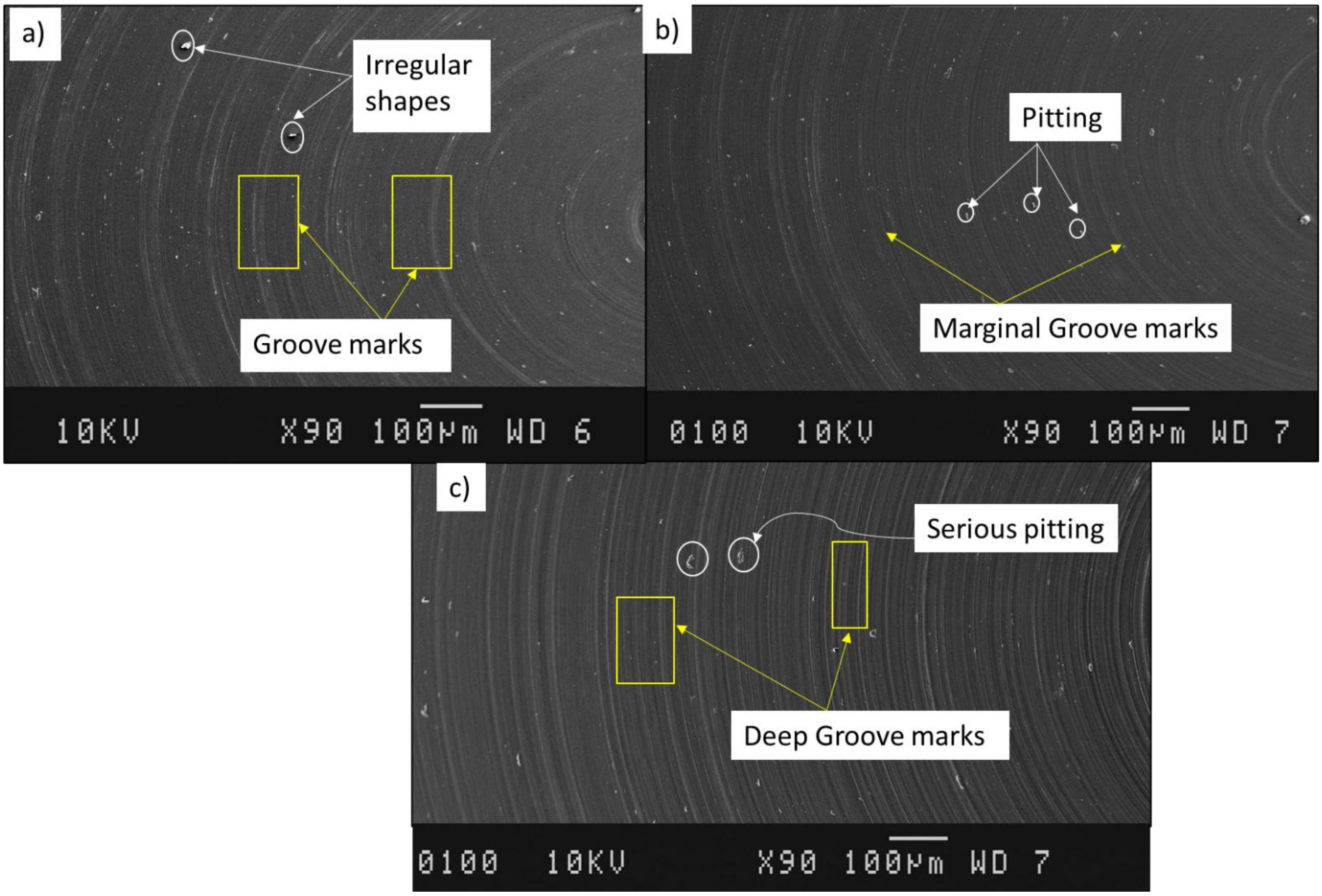


Figure 5. Typical surface morphology of the diamond turned samples at different feed rates a) 10 mm/min b) 5 mm/min c) 1 mm/min.

Fig 6 provides clear images obtained from a Scanning Electron Microscope (SEM) before machining and after the final cut, serving to validate the occurrence of tool wear. Fig. 6 (a) shows the diamond tool before machining where the edge is clear with no signs of tool wear. Whereas, Fig. 6 (b) the diamond tool showed after machining of AM Ti-6Al-4V alloy has some significant micro-fractures and flank wear is also observed, while no crater wear is detected. These micro-fractures can cause serious damage to the surface roughness of the costly substrate. It can also be observed that the cutting edge becomes less sharp compared to unused regions. The results obtained from the SEM photographs demonstrate the possibility of condition monitoring on tool wear using the proposed DWT based on a standard deviation of vibrational signals.

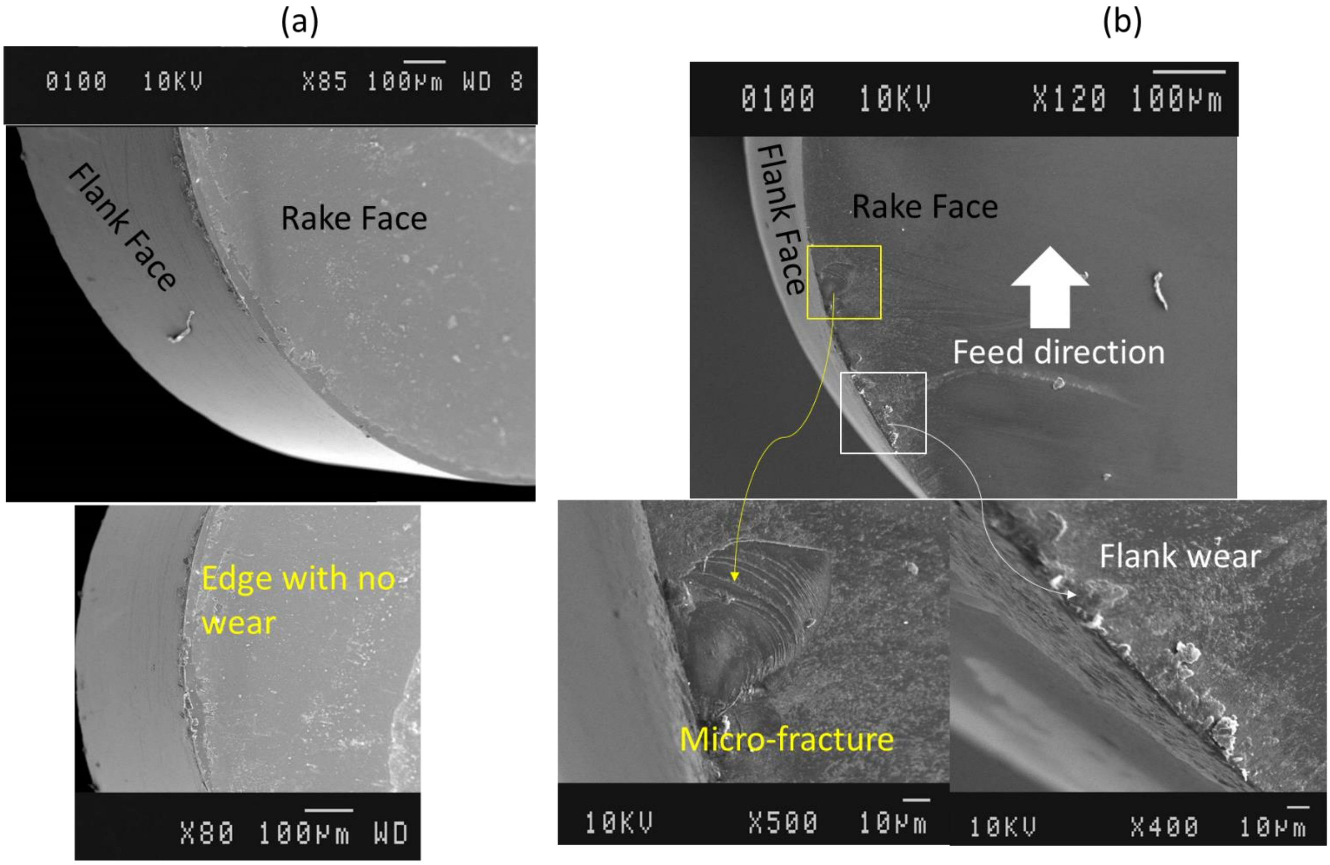


Figure 6. SEM photographs of diamond tool edge a) Before machining b) After machining of Ti-6Al-4V alloy

5 Conclusions

The paper presents a quantitative analysis of tool wear in diamond turning of AM Ti-6Al-4V utilizing vibrational signals. The outcomes of the study are summarized below:

- Vibrational signals acquired during diamond turning are analysed using the discrete wavelet transform. It has been observed that the Daubechies (dB4) mother wavelet exhibits a strong correlation in monitoring tool wear.
- Analysis of 8-level decomposition approximation graph clearly visualizes the abrupt variations in the used and fresh tools during various feed rates.
- The standard deviation analysis of the fresh and used tools, showed the variations are minimum at 5 mm/min and maximum at 1 mm/min.
- Also, SEM images analysis is carried to understand the micro facture and tool wear in the flank face of the diamond tool.

Finally, DWT has proven to be a robust method for vibrational signal processing to monitor the tool wear without other information sources. This study will further lay the foundation for the tool condition monitoring and real-time surface finish monitoring in diamond turning using time-frequency analysis.

Declaration of conflicting interests

The authors declare that there is no conflict of interest.

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