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Analysis of Regenerative Raw Signals Using Variational Mode Decomposition

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ABSTRACT

Faults like regenerative tool chatter have been evaluated by several researchers in order to suppress its adverse effect. However, many facets of this domain are yet to be addressed. In the present work, a new methodology has been proposed to process the recorded regenerative chatter signals in order to extract the chatter features. In the proposed approach, experiments have been performed and signals pertaining to regenerative tool chatter have been recorded using microphone. Thereafter, the recorded signals have been evaluated and preprocessed using variational mode decomposition (VMD) in order to extract chatter features. The decomposed signals that result in variational mode functions have been further evaluated by calculating a response termed as chatter index. This response has been used to predict the chatter severity during machining at different combinations of input parameters, on verifying the obtained results it has been found that the proposed methodology is significant in identifying the chatter severity.

1. INTRODUCTION

Nowadays, fault diagnosis is very essential and trending. A lot of signal processing techniques have been adopted by researchers in order to identify faults in machinery. The faults can be of any type including fault in bearings, gears, moving part, surface finish or tool failure [1-7]. The adopted signal processing technique should have the capability to identify the exact fault. The selection of techniques is a very essential step in the due process. The researchers in the past have done the selection on the basis of the type of signal and feature to be extracted. The popular techniques used till date are peak to peak analysis [8], wavelet [9-11], short time-frequency transform (STFT) [12], Hilbert Huang transform (HHT) [5, 13, 14], Fourier transform (FT) [15, 16], empirical mode decomposition (EMD) [17, 18], and ensemble empirical mode decomposition (EEMD) [3, 19, 20]. The selection of appropriate signal processing technique depends on the type of feature we want to extraction, for time information peak to peak analysis is preferred. For frequency information, Fourier transform is adopted. However, for both time and frequency information short-time Fourier transform (STFT), wavelet transform (WT), Hilbert Huang transform (HHT), empirical mode decomposition (EMD) and ensemble empirical mode decomposition (EEMD). Recently, a researcher has discussed in his work that, from the above mentioned time-frequency techniques, wavelet, STFT are suitable for non-stationary and linear signal. HHT, EMD and EEMD are suitable for non-stationary and nonlinear signals. However, for different signals, the efficiency of the technique may vary. In the case of raw chatter signals, the signal is usually associated with unwanted noise and contaminations. In order to filter out, these contaminations an appropriate signal processing techniques need to be adopted. In 2019, Shrivastava et al. have used EMD in order to sieve out the contaminations from the recorded tool chatter signals. They have found that EMD is suitable for processing the raw chatter signals but sometimes due to the mode mixing phenomenon, the extraction of exact features is affected. Hence, they reported EEMD as a more effective alternative [21]. Later, in 2020 it has been reported that being EEMD more effective that EMD it also has certain issues like the involvement of noise contents in the filtered signals [19]. These noise contents are associated with the noise that is added to the signal intentionally during the decomposition using EEMD. However, no appropriate technology has been implemented to the raw chatter signals in order to rectify such a problem. Hence, in the present work, the variational mode decomposition (VMD) technique has been adopted and implemented to the raw chatter signals.

VMD technique mainly decomposes a signal into sets of sub-signals called as variational mode functions (VMFs) [22]. It efficiently separated the non-linear, non-stationary and noisy signals into sub-signals according to the frequency range. The VMD technique does not prefer any sifting mechanism for the decomposition procedure, because of which VMD never faces the problem of mode mixing. VMD comprises the benefits of Wiener filtering and Hilbert transform, hence it provides more accurate and precise decomposition results.

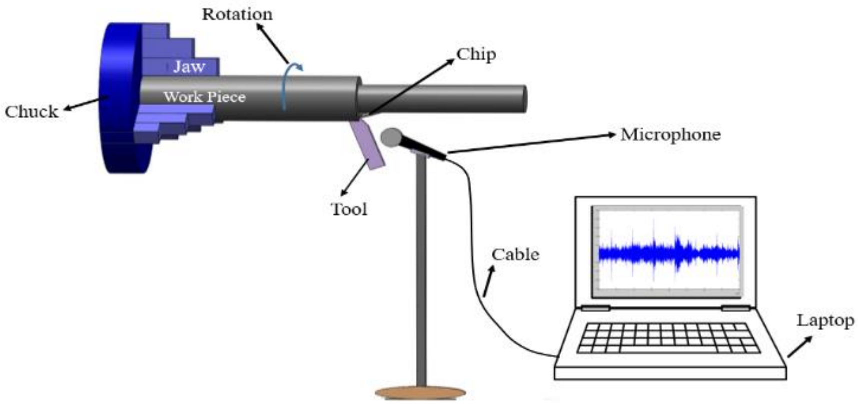

Figure 1. Turning operation with acquisition setup

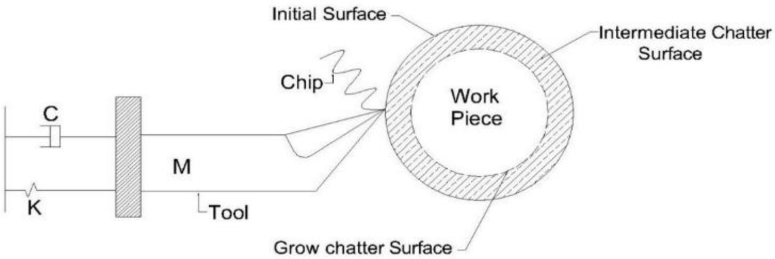

Figure 2. Mechanism of chatter regeneration

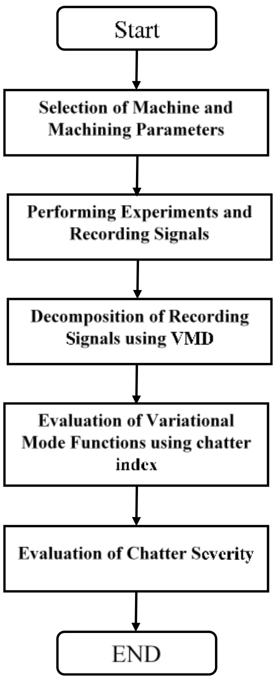

Figure 3. Proposed methodology

The decomposed signals have been further evaluated in order to extract the chatter features. In the current work, the process that has been monitored is the turning operation performed on CNC trainer lathe. The idea behind the monitoring is the extraction of features associated to regenerative chatter. In order to understand the monitoring and feature extraction process it is essential that understand the term regenerative chatter. In machining process specifically in CNC lathe (turning operation), a workpiece is processed by a single point cutting tool. During the machining process the tool is fed forward and the workpiece rotated with a desired speed at its own place as shown in Figure 1.

During the process, it is usually assumed that the tool should be harder than the workpiece and the workpiece should have a uniform composition or in other words, the workpiece is considered as homogeneous in nature. However, it has been reported by researchers that the work material (any alloy or similar material) cannot be perfect homogeneous due to the fact that its composition will always vary in small proportion at different places [23]. The variation in composition gave rise to an unavoidable process that has been named as regenerative chatter [24]. This regenerative chatter initiates due to the variation in the material composition, due to which the tool experiences a sudden jerk and this jerk lead to the generation of wavy profile. The wavy profile so generated on the surface of workpiece tends to increase its waviness with the number of revolutions during turning and hence regenerates the waviness again and again throughout the process as shown in Figure 2.

This regenerative chatter hampers the surface quality of the workpiece. In the current work, the signals associated with this regenerative effect have been recorded using a non-contact type sensor specifically, a microphone.

Moreover, for the ease of understanding the proposed methodology has been drawn in the form of the flow chart as shown in Figure 3.

2. METHODS AND MATERIALS

2.1 Materials

The material used for turning operation is low carbon steel AISI 1018 in the form of a bar having dimensions Length: 85

mm, Diameter: 33 mm. The machine used for turning operation is trainer lathe, model-MCL10 (CNC type). The cutting condition (input parameters and levels) adopted have been shown in Table 1. The specification of the tool has been shown in Table 2. During the machining of the workpiece, the signals generated have been recorded with the help of a microphone. Table 3 contains the specification of the microphone. The actual image of the machining setup has also been provided in Figure 4.

Table 1. Selected machining parameters and levels

Parameters	Level 1	Level 2	Level 3
d, Depth of cut, mm	0.5	1	1.5
s, cutting speed, m/min.	150	200	250
f, feed rate, mm/rev.	0.15	0.20	0.25

Table 2. Specification of tool

Cutting insert	Tungsten carbide

Table 3. Specification of microphone

Generic name	AGN-480 (AHUJA)
Domain	Dynamic Microphone (Unidirectional)
Frequency	50-10,000 Hz.
Sensitivity	2.0 mV/Pa
Impedance	600 Ω
Overall Length	470mm

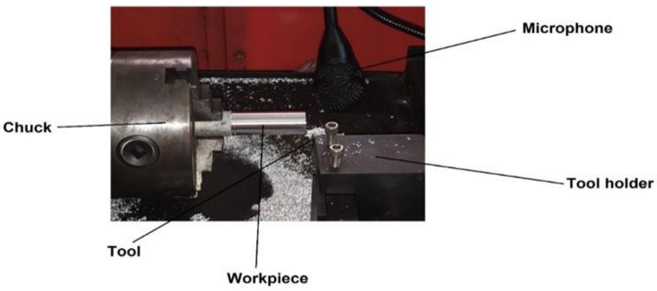

Figure 4. Actual machining setup

2.2 Methods

After recording the chatter signals these signals have been treated using VMD in order to filter out the contaminations from the signal. The adopted signal processing technique is an advanced method developed in order to resolve the limitations of ensemble empirical mode decomposition [21, 22]. After decomposing the signals the obtained variational mode functions have been used to determine the chatter index.

2.2.1 Chatter Index

The term chatter index refers to the deviation of amplitude from mean [25]. The formula invoked in the calculation of the chatter index has been shown in Eq. (1).

$$CI = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(x(t)-\mu)^2} \tag{1}$$

where, N resembles the signal length, μ is the mean of amplitude.

3. EXPERIMENTATION

For experimentation CNC lathe have been used. The combination used for the experiments has been developed considering the full factorial design of the parameters and levels shown in Table 4. During each experiment, the generated signals have been acquired. These signals have been decomposed using VMD to obtain the VMF's. One of the recorded signal and its corresponding VMF's have been shown in Figures 5 and 6. Figure 5 represents the recorded signal. From the signal, it is clear that the amplitude of the signal is maximum at around 40 dB. However, it may be due to chatter or any other contamination in the signal. Hence, in order to sieve out the contaminations, VMD has been used. One of the preprocessed signals has been shown in Figure 6. In Figure 6 the VMFs resemble the variational mode functions that are generated on the decomposition of the signal, from the 6 IMFs any one of the modes may be responsible for chatter. Hence, the Fourier transform of the modes has been done to obtain the magnitude. The obtained modes (1 to 6) and their corresponding Fourier transform has been shown in Figure 6 (a) to Figure 6 (f).

The frequency-domain of the VMFs have analyzed by monitoring the peak in magnitude and cluster of frequencies. The mode with maximum magnitude has been marked and the corresponding amplitudes of the IMF have been extracted. In the same way, 27 different VMFs have been determined and the corresponding range of amplitudes has been collected. These amplitudes have been analyzed and CI has been calculated as listed in Table 4. Further, the response CI has been used to calculate the chatter severity.

Table 4. Full factorial design and calculated values of responses

Experiment No.	d	s	f	CI
1.	0.5	150	0.15	1.135
2.	0.5	150	0.20	1.741
3.	0.5	150	0.25	1.132
4.	0.5	200	0.15	0.255
5.	0.5	200	0.20	1.109
6.	0.5	200	0.25	0.643
7.	0.5	250	0.15	0.699
8.	0.5	250	0.20	2.358
9.	0.5	250	0.25	2.762
10.	1.0	150	0.15	0.913
11.	1.0	150	0.20	1.431
12.	1.0	150	0.25	0.744
13.	1.0	200	0.15	3.169
14.	1.0	200	0.20	1.235
15.	1.0	200	0.25	1.845
16.	1.0	250	0.15	1.567
17.	1.0	250	0.20	1.221
18.	1.0	250	0.25	2.744
19.	1.5	150	0.15	1.554
20.	1.5	150	0.20	1.540
21.	1.5	150	0.25	1.642
22.	1.5	200	0.15	1.578
23.	1.5	200	0.20	0.664
24.	1.5	200	0.25	0.605
25.	1.5	250	0.15	3.764
26.	1.5	250	0.20	4.361
27.	1.5	250	0.25	4.128

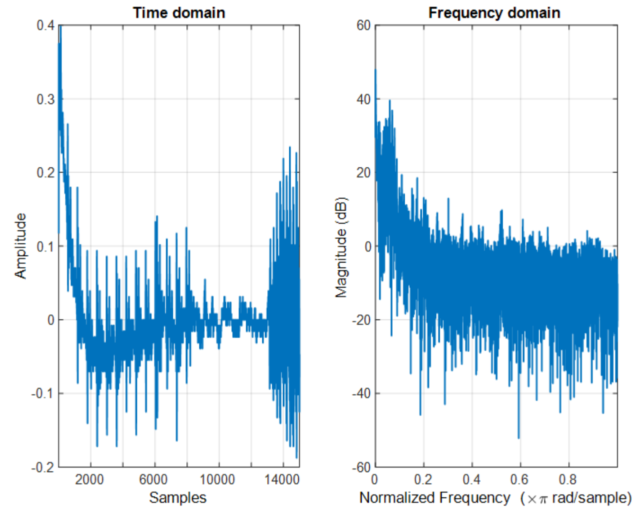

Figure 5. Recorded signal and its Fourier transform

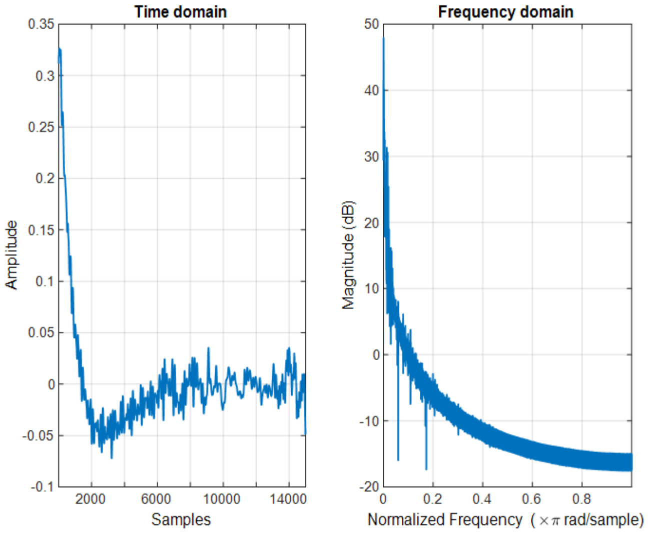

Figure 6(a). Mode 1 and its Fourier transform

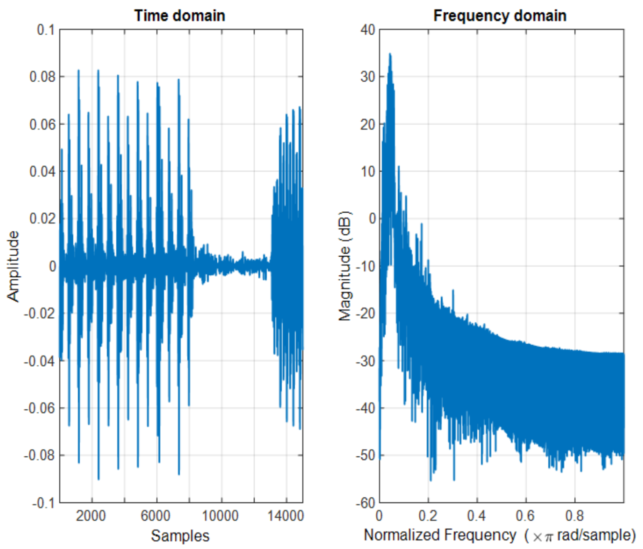

Figure 6(b). Mode 2 and its Fourier transform

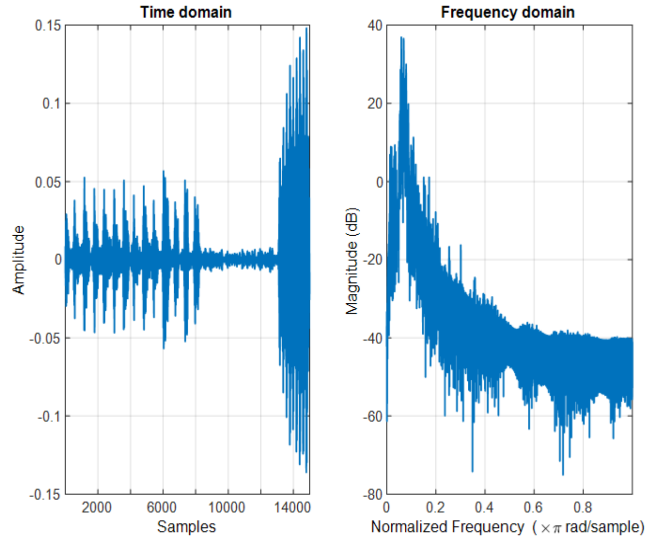

Figure 6(c). Mode 3 and its Fourier transform

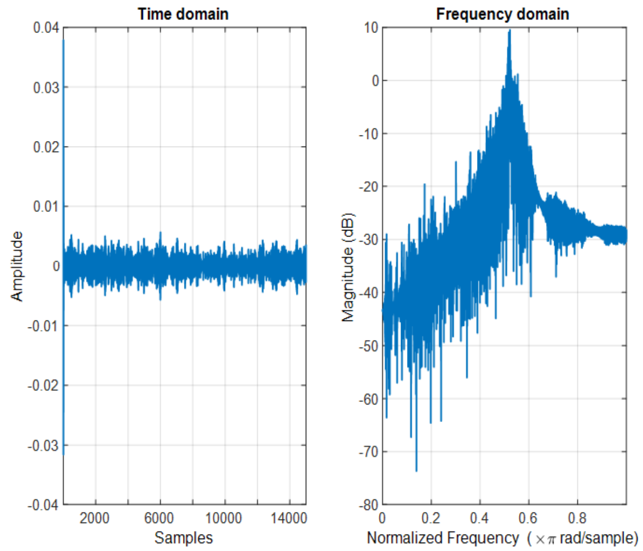

Figure 6(d). Mode 4 and its Fourier transform

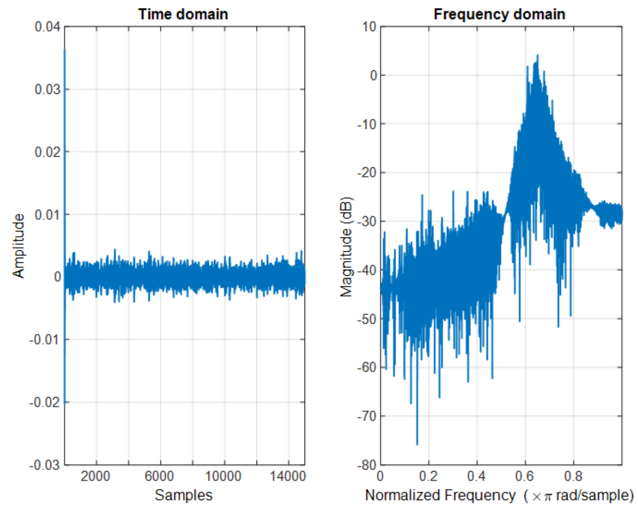

Figure 6(e). Mode 5 and its Fourier transform

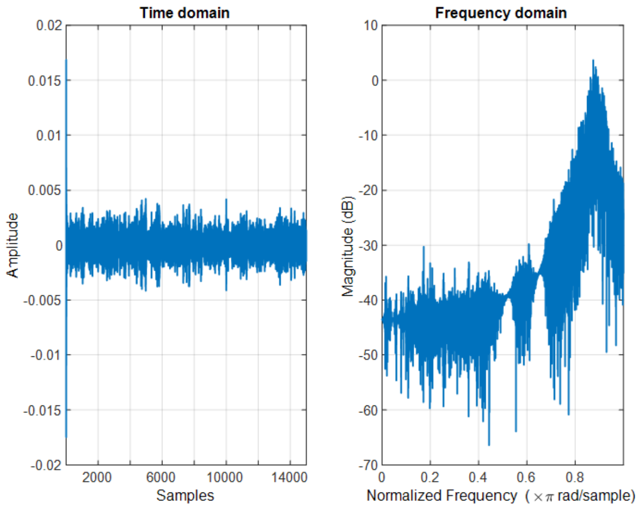

Figure 6(f). Mode 6 and its Fourier transform

4. RESULTS AND DISCUSSION

The obtained variation modes as shown in Figure 6(a) to Figure 6(f) shows that the magnitude of each mode varies very differently. In the case of mode 1, the maximum magnitude is around 50 dB, in the case of mode 2 it is around 35 dB, in the case of mode 3, it is around 38 dB. However, in the remaining 3 modes, the magnitude is very low between 10 to 1 dB. The variation in mode resembles the effect of that particular segment of the signal in chatter. Higher the magnitude more will be the chatter. It has also been observed that modes 5 and 6 are relatively similar. This indicated that saturation in modes has arrived, which means the extraction of more modes will be useless or redundant. The decomposed signals obtained have been evaluated using CI. The obtained CI values have been listed in Table 4. From the table, it has been obtained that the maximum value of CI is for experiment number 26 and the minimum value of CI is for experiment number 4. Hence, for experiment number 4 minimum chatter marks will be observed. However, for experiment number 26 maximum chatter marks will be observed. Accordingly, the chatter severity can be obtained by arranging the values of the chatter index in increasing order. In order to identify the variation in the chatter index with respect to the experiment, the plot has been drawn showing the variation of CI with respect to experiments as shown in Figure 7.

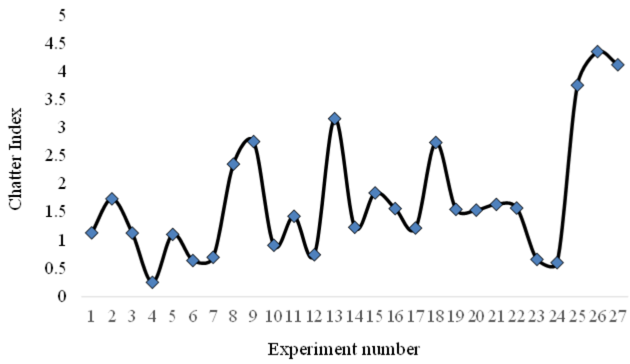

Figure 7. Experimental run versus chatter index

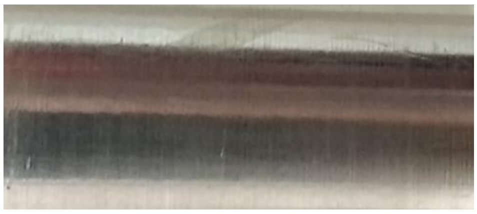

Figure 8. Surface topography of workpiece for experiment number 4

Figure 9. Surface topography of workpiece for experiment number 26

Moreover, in order to verify the proposed methodology. The cutting combinations providing minimum and maximum chatter have been physically examined. The images of the surface view have been shown in Figures 8 and 9. Figure 8 represents the surface topology of the workpiece machined at input combinations of experiment 4 (refer Table 4). Figure 9 represents the surface topology of the workpiece at input combinations of experiment 26. From the figures, it is very clear that Figure 9 have more chatter marks as compared to the surface shown in Figure 8. This verifies that the proposed methodology is significant and the methodology can be adopted for predicting the nature of chatter during machining.

5. CONCLUSIONS

The proposed methodology works on the investigation of regenerative chatter during turning operations. In the current work, experimentation has been done and chatter signals have been acquired. These signals have been processed using variational mode decomposition technique. Thereafter, the signal has been evaluated in order to calculate chatter severity.

The findings of the works are:

(1) The acquired signals (raw chatter signals) have been processed successfully using variational mode decomposition.

(2) Chatter index benefits in revealing the tendency of chatter.

(3) From the 27 experiments, the minimum value of CI obtained is 0.225 for experiment number 4, and the maximum value of CI is 4.361 for experiment number 26.

(4) On verifying the obtained results it has been found that the proposed methodology is significant in identifying the chatter severity.

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