Cluster Analysis using I-kaz Coefficient to Assist Machining Monitoring Process

Nuawi M. Z., Lamin F., Abdullah S., Nor M. J. M., Arifin A.

Abstract— Dynamic state recognition and event-prediction are fundamental tasks in signal processing. This paper presents a novel identification method which could form the basis for forecasting a generalized machining condition. The method relies on the value of I-kaz coefficient, which is an extractable unique feature that can be gained for every signal acquired during the cutting process. The method is useful for classifying the acquired signal in the machining process to a set of cluster which may represent the specific cutting condition of the machining process. The classification method was succeeded in identifying the cutting parameter that being used to generate the signal, which was the combination of the cutting speed, feed rate and depth of cut. This kind of clustering is very useful in the analysis of machining signal processing such as signal conformation, fault identification and etc.

Keywords— I-kaz, Statistical parameter, Machining, Signal clustering, Cutting parameter.

I. INTRODUCTION

THE concept of tool condition monitoring has gained considerable importance in the manufacturing industry, as it significantly influences the manufacturing process economy and the machined part quality [1]. This is mainly attributed to the transformation of the manufacturing environment from manually operated production machines to the highly automated machining operation. Thus, the analysis and monitoring of machining condition is a challenge with growing importance in order to achieve the fully automated production. A reliable monitoring system could allow optimum utilisation of the tool life, which is highly desirable. In response to the need of tool condition monitoring, techniques such as fault monitoring, clustering, detection, and diagnosis have become increasingly essential [2, 3].

The clustering approach was intensively used in biomedical practice. In the previous study, the clustering approach has been applied for many fields of medicine ranging from biomedical basic research to clinical assessment of patient data to determine health condition [4, 5]. Although there are obvious methodological similarities, each application requires specific careful consideration with regard to data pre-processing, post-processing and interpretation [5]. In view of this, the clustering approach can be simulated in the tool condition monitoring application for fault detection. The main aim of most clustering techniques is to obtain useful information by grouping data in clusters which within each cluster the data exhibits similarity [6]. Clustering algorithms are used extensively not only to organize and categorize data, but are also useful for data compression and model construction [6]. Clustering is useful in several exploratory pattern-analysis, grouping, decision-making, and machine-learning situations, including data mining, document retrieval, image segmentation, and pattern classification [7]. However, in many such problems, there is little prior information available about the data, and the decision-maker must make as few assumptions about the data as possible. It is under these restrictions that clustering methodology is particularly appropriate for the exploration of interrelationships among the data points to make an assessment of their structure [7]. Besides, clustering plays an important role in some applications such as signal confirmation, interference identification, spectrum management and etc.

In general, classification can be approached either from a decision-theoretic or statistical pattern recognition framework [8]. The decision-theoretic based classification can be very complex depends on the number of unknown parameters that were associated [8]. For that reason, the statistical pattern recognition approach has been considered in this study, as only the effect of cutting parameters to the measured signal was considered as the scope of this study.

In this paper, a statistical pattern recognition-based classification was presented. In particular, the clustering will be determined based on the plot of the I-kaz coefficient, the skewness and the kurtosis value for some selected cutting conditions, which were carried out using different cutting

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speed, feed rate and depth of cut. This wide scope of completely different cutting condition illustrates the flexibility of the I-kaz coefficient, the skewness and the kurtosis value in clustering signal. Hence, this kind of approach can assist the monitoring process and the determination of fault symptom can be done accordingly.

II. Literature Background

For the clustering purpose, the measured signal was analysed in terms of its statistical feature. The statistical feature was extracted from the measured signal by means of the statistical parameter value. The statistical parameter that was utilised for classifying signal in this study was selected based on the ability of the statistical parameter to represent the machining process. Since the machining process was such a complex nature, any changes of any cutting parameter influence the tool wear by a large extent [9]. Because of the complexity of the machining operation, it requires a flexible, lucid and adaptive parameter to be applicable in the monitoring applications [10]. Thus, skewness, kurtosis and I-kaz coefficient value for each acquired signal was considered. The skewness parameter as defined in Eq. (1) exhibits the asymmetry of the probability distribution of a real-valued random variable of data.

$$S = \frac{1}{n(r.m.s)^3} \sum_{i=1}^{n} \left(x_i - \bar{x}\right)^3 \qquad (1)$$

where S is the skewness, n is the number of data, *r.m.s.* is the root mean square value, x_i is the value of data at the instantaneous point and $\bar{x}$ is the mean value.

The kurtosis parameter was considered as it generally used in engineering for detection of fault symptoms because of its sensitivity to high amplitude events [11]. The kurtosis value is approximately 3.0 for a Gaussian distribution. Higher kurtosis values indicate the presence of more extreme values than should be found in a Gaussian distribution. Kurtosis, which is the signal 4th statistical moment, is a global signal statistic which is highly sensitive to the spikiness of the data. For a discrete data set the kurtosis value is defined as in Eq. (2):

$$K = \frac{1}{n\sigma^4} \sum_{i=1}^{n} (x_i - \bar{x})^4 \qquad (2)$$

where K is the kurtosis, n is the number of data, σ is the standard deviation, x_i is the value of data at the instantaneous point and $\bar{x}$ is the mean value.

Besides, the I-kaz analysis, which was introduced by Mohd Zaki *et al.* [12] was utilised in this study. Based on the I-kaz analysis, the time domain signal is decomposes into three frequency ranges, which are:

(i) x-axis : low frequency range (*LF*) of 0-0.25 f_{max}

(ii) y-axis : high frequency range (*HF*) of 0.25 f_{max} – 0.5 f_{max}

(iii) z-axis : very high frequency (*VF*) range of 0.5 f_{max}.

where f_{max} is the maximum frequency span of the measured signal. The calculation of the maximum frequency span is stated in Eq. (3).

$$f_{\max} = \frac{f_s}{2.56} \qquad (3)$$

where f_s is the sampling frequency and 2.56 is the Nyquist number.

The effect of I-kaz coefficient, Z^{∞} on the machining condition was taken into consideration in order to cluster signals. The Z^{∞} value was proven to be a good parameter in clustering signal as it exhibits a unique clustering pattern compared to the other statistical parameter such as skewness and kurtosis [13]. The I-kaz coefficient, Z^{∞} can be calculated as in Eq. (4):

$$Z^{\infty} = \frac{1}{n}\sqrt{K_L s_L^4 + K_H s_H^4 + K_V s_V^4} \qquad (4)$$

where n is the number of data, K_L, K_H, K_V are the kurtosis of signal in *LF*, *HF* and *VF* range and s_L, s_H and s_V are the standard deviation of signal in *LF*, *HF* and *VF* range respectively.

III. Methodology

Sound signal was measured 10 cm from the cutting zone using a high frequency microphone during several machining tests which was done until the tool life criterion of the uncoated carbide cutting tool exceeded. Based on ISO 3685:1993 [14], the flank wear value of 0.3mm was recommended in defining tool life end-point criterion for turning process. The machining tests were carried out on a Cincinnati Milacron 200T Turning Centre machine in dry condition. The data acquisition process was shown in Fig. (1).

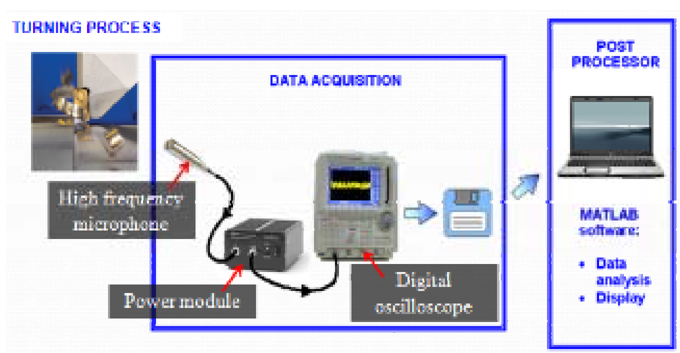


Figure 1. The data acquisition process of the sound signal generated from the turning operation

In general, changes in cutting speed, feed rate and depth of cut affect the generated signal during the turning process [9]. For that reason, twelve combinations of those cutting parameters were taken into consideration. The details of the parameters were presented in Table 1. Generally, the parameters were divided into six sets of test sample which each set was comprised of similar value of feed rate and depth of cut. The reason of creating this kind of cutting parameter grouping was to simplify the clustering. With that intention, the number of significant probabilities can be accordingly reduced for the interpreting task.

Table 1 The set of test samples used i.e. twelve combination of cutting speed, V_c, feed rate, f and depth of cut, D_c.

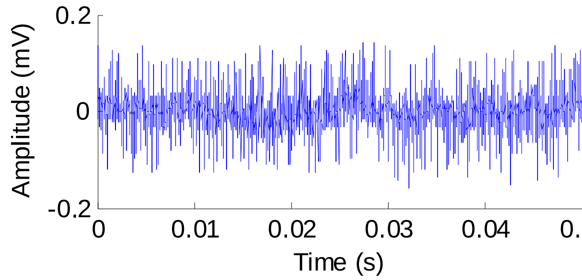
No. of set	f *(mm/rev)*	D_c *(mm)*	V_c *(m/min)*	No. of test sample
SET 1	0.2	0.2	105	1
			120	2
SET 2	0.25	0.2	105	3
			120	4
SET 3	0.25	0.25	105	5
			120	6
SET 4	0.2	0.25	105	7
			120	8
SET 5	0.25	0.15	105	9
			120	10
SET 6	0.2	0.15	105	11
			120	12

Since every signal generated from the turning operation was affected by the changes in cutting parameters, the statistical analysis was done in order to classify the signal based on its statistical feature. Therefore, the I-kaz coefficient, the skewness and the kurtosis were calculated for each signal that acquired from the machining test. All the values gained were then plotted in two different types of plot i.e. I-kaz coefficient against skewness and I-kaz coefficient against kurtosis. The pattern of data that scattered in both plots were then analysed in order to identify the formation of any significant clustering.

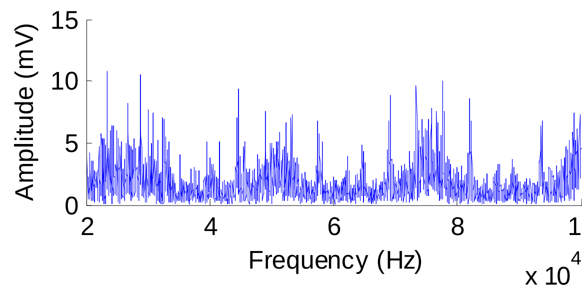
IV. Results and Discussions

As mentioned in the methodology section, two types of plot were done in this study i.e. I-kaz coefficient against skewness and I-kaz coefficient against kurtosis. Both type of plot were defining I-kaz coefficient as the responding variable. This is mainly because it was the most reliable statistical parameter especially for monitoring purpose where the observation on the changes of the signal amplitude and frequency were commonly required [12].

For examples, Fig. (2) to Fig. (7) show some signals that have been measured during the machining tests. The signals were presented in time and frequency domain. The frequency domain signal was obtained by transforming the measured signal which was in time domain using Fast Fourier Transform (FFT) algorithm. Based on the figures, the differences between the signals in terms of amplitude and frequency can be observed for different test sample.

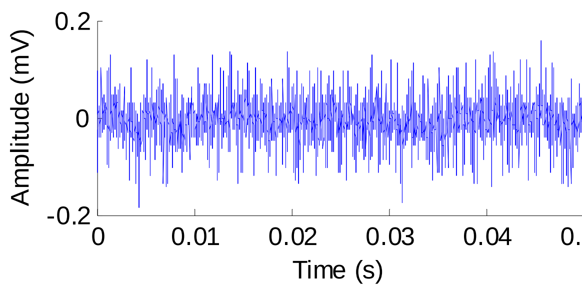


(a)

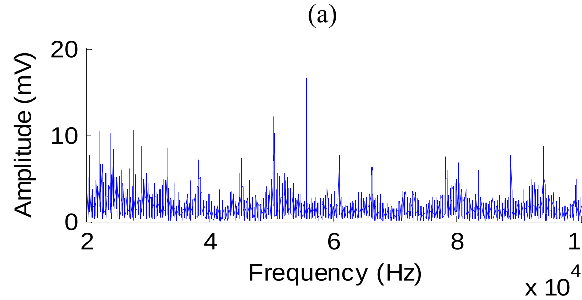


(b)

Figure 2. Example of signal that generated while machining using the 1st machining set: (a) time domain, (b) frequency domain



(a)



(b)

Figure 3. Example of signal that generated while machining using the 2nd machining set: (a) time domain, (b) frequency domain

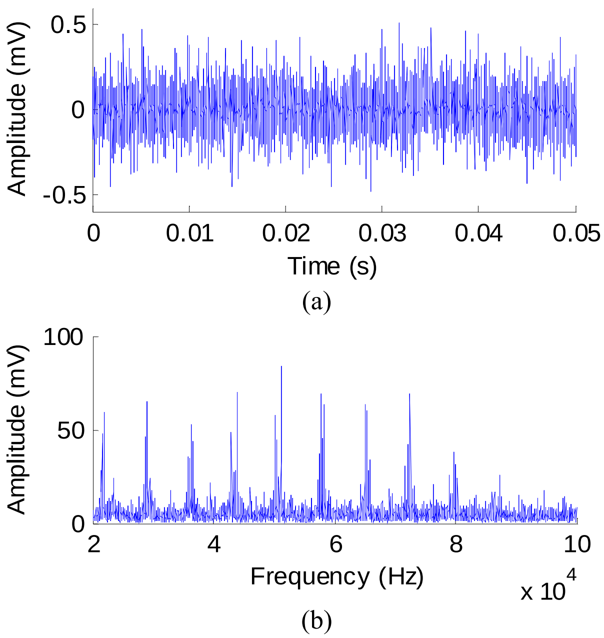


Figure 4. Example of signal that generated while machining using the 3rd machining set: (a) time domain, (b) frequency domain

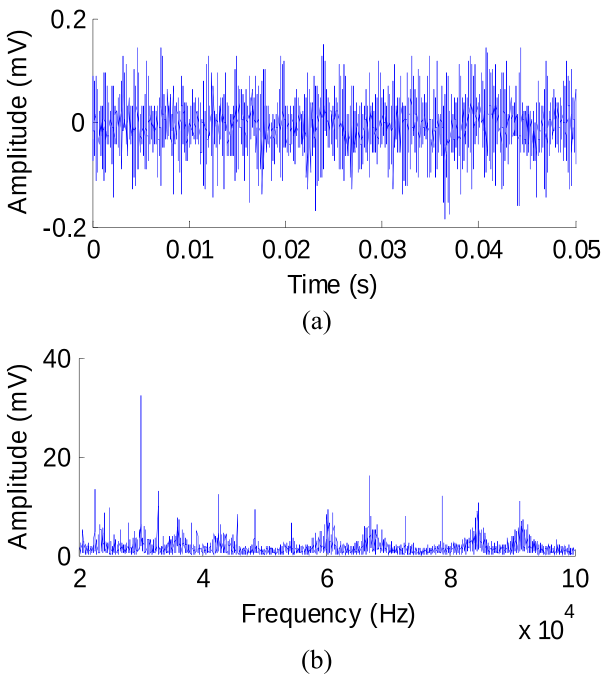


Figure 5. Example of signal that generated while machining using the 4th machining set: (a) time domain, (b) frequency domain

A. I-kaz coefficient Vs Skewness

Machining condition was strongly correlated with the sound emitted during the machining process [15-17]. In view of this, the statistical parameter was calculated to characterize the

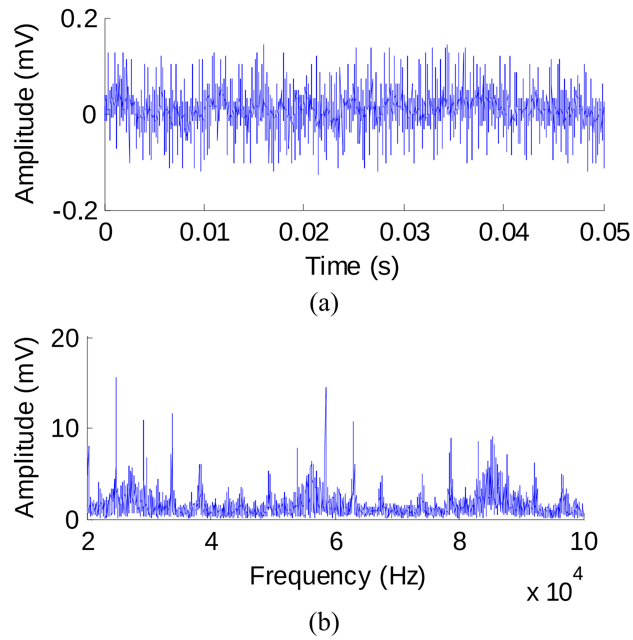


Figure 6. Example of signal that generated while machining using the 5th machining set: (a) time domain, (b) frequency domain

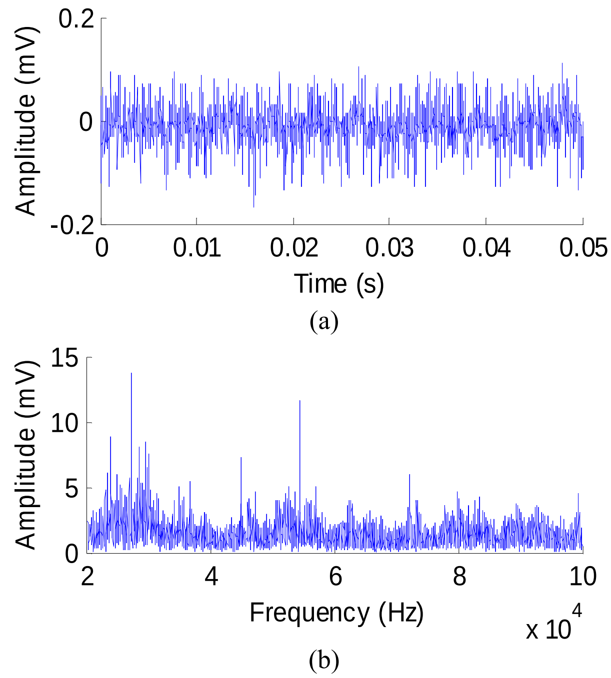


Figure 7. Example of signal that generated while machining using the 6th machining set: (a) time domain, (b) frequency domain

measured signal. Based on the Eq. (1) and (4), the S and Ƶ$^{\infty}$ value obtained from the twelve set of turning test was varies between 2.22×10^{-10} and 1.31×10^{-7}. Since all the signals generated from the turning process are positive skewed, it confirm that the signal is turning [18]. The Z^{∞} value was then plotted against S value for each set of machining test as shown in Fig. (8).

In every machining set, the feed rate, f and the depth of cut, D_c were kept constant while only changing the parameter of cutting speed, V_c for every test sample. Nevertheless, the predisposition of signal to be scattered in clusters based on the specific test sample still can be observed obviously. This kind of clustering can be applied when signal confirmation is required in machining monitoring process. Thus, the reliability of the measured signal can be verified accordingly. Subsequently, detail inspection can be done if there is any faulty signal found during the monitoring process.

B. I-kaz coefficient Vs Kurtosis

From the Eq. (2) and (4), the K and Z^{∞} value has been calculated for each measured signal. As results, the value of K varies from 2.87 to 11.35 while the value of Z^{∞} varies from 1.48 x 10-9 to 9.28 x 10-7. Based on these statistical values, Z^{∞} has been plotted against K. The plot of Z^{∞} against K based on the different feed rate exhibits a unique clustering pattern.

As shown in Fig. (9), the blue region was comprised of signal that generated while performing cutting at 0.2 mm/rev feed rate i.e. the 1st, 4th and the 6th set of cutting parameter. Meanwhile, the red region was comprised of signals that generated by 0.25 mm/rev feed rate, i.e. signals that generated using the 2nd, 3rd and the 5th set of cutting parameter. It can be observed that the red region was obviously isolated, obtaining the upper and the lower region of 0.25 mm/rev feed rate. This isolated clustering pattern was caused by the different depth of cut value. As the cutting process performed at the higher depth of cut value ($D_c \geq 0.2$), the generated signal was located at the upper red region. Otherwise, signals that generated by the lower depth of cut value ($D_c \leq 0.15$) was

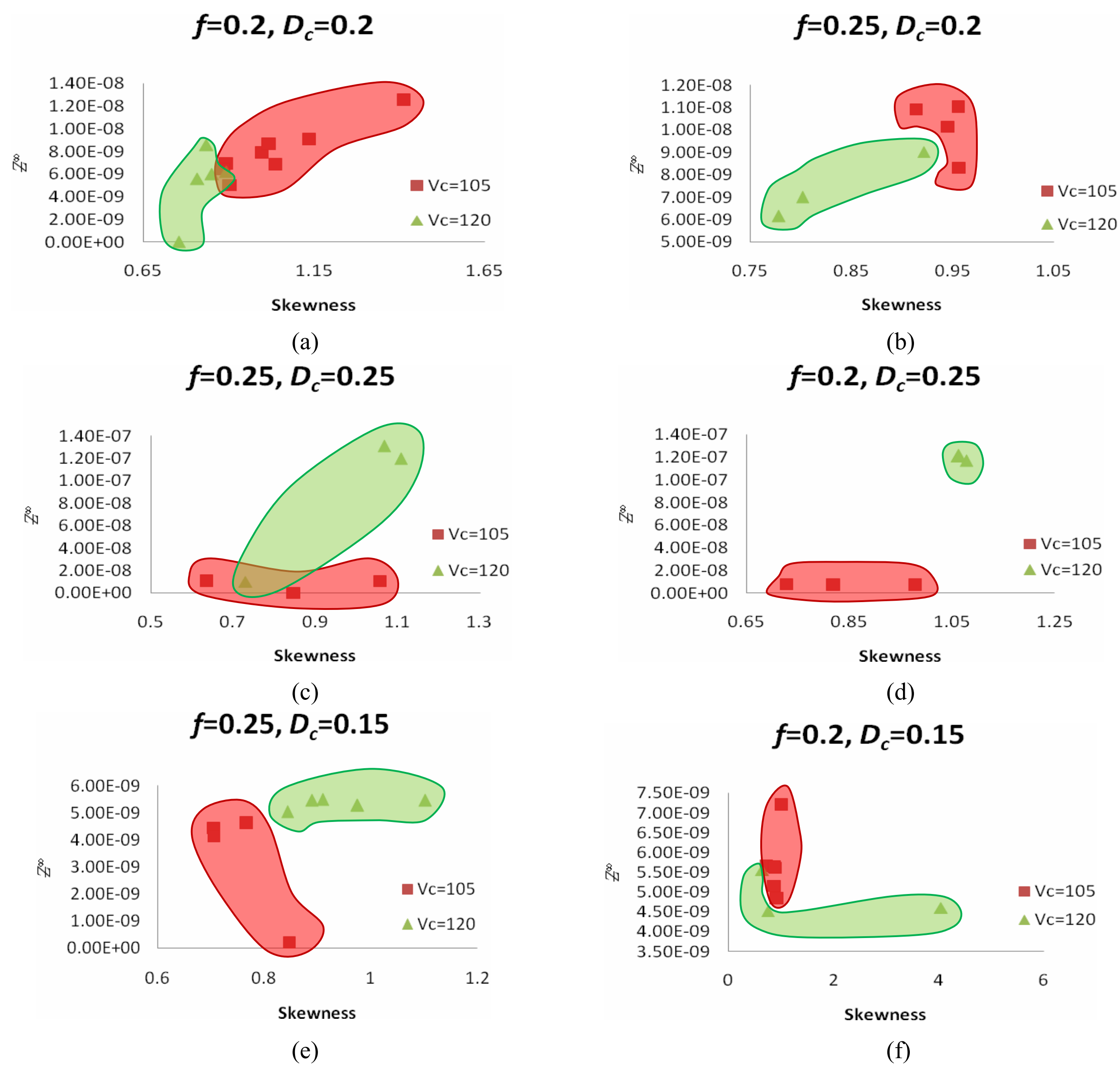


Figure 8. The plot of I-kaz coefficient againts skewness for different set of machining test: (a) Set 1, (b) Set 2, (c) Set 3, (d) Set 4, (e) Set 5, (f) Set 6.

located at the lower red region.

For a better reasoning purpose, the Ƶ$^{\infty}$ values gained were then plotted against the K values based on the similar depth of cut and cutting speed separately. Fig. (10) shows some sets of cluster that have been obtained for different depth of cut and cutting speed value. Based on the certain value of cutting speed and depth of cut, the signals can be well clustered. From this finding, the 5th and the 6th set of cutting parameter (see Fig. 10(a) and 10(b)), which both have 0.15 mm depth of cut clearly indicates the lower region of 0.25 mm/rev feed rate in Fig. (9). Therefore, Fig. (9) can be used as a general clustering pattern and the Fig. (10) can be used to analyse the signal at particular feed rate, depth of cut and cutting speed.

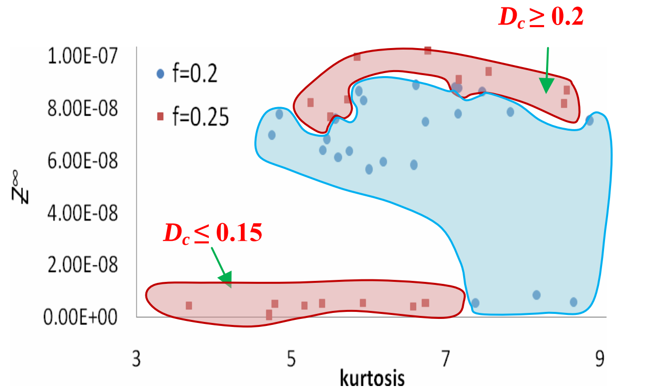


Figure 9. The signal clustering based on the 0.2 mm/rev and 0.25 mm/rev feed rate for the 18 sets of test sample

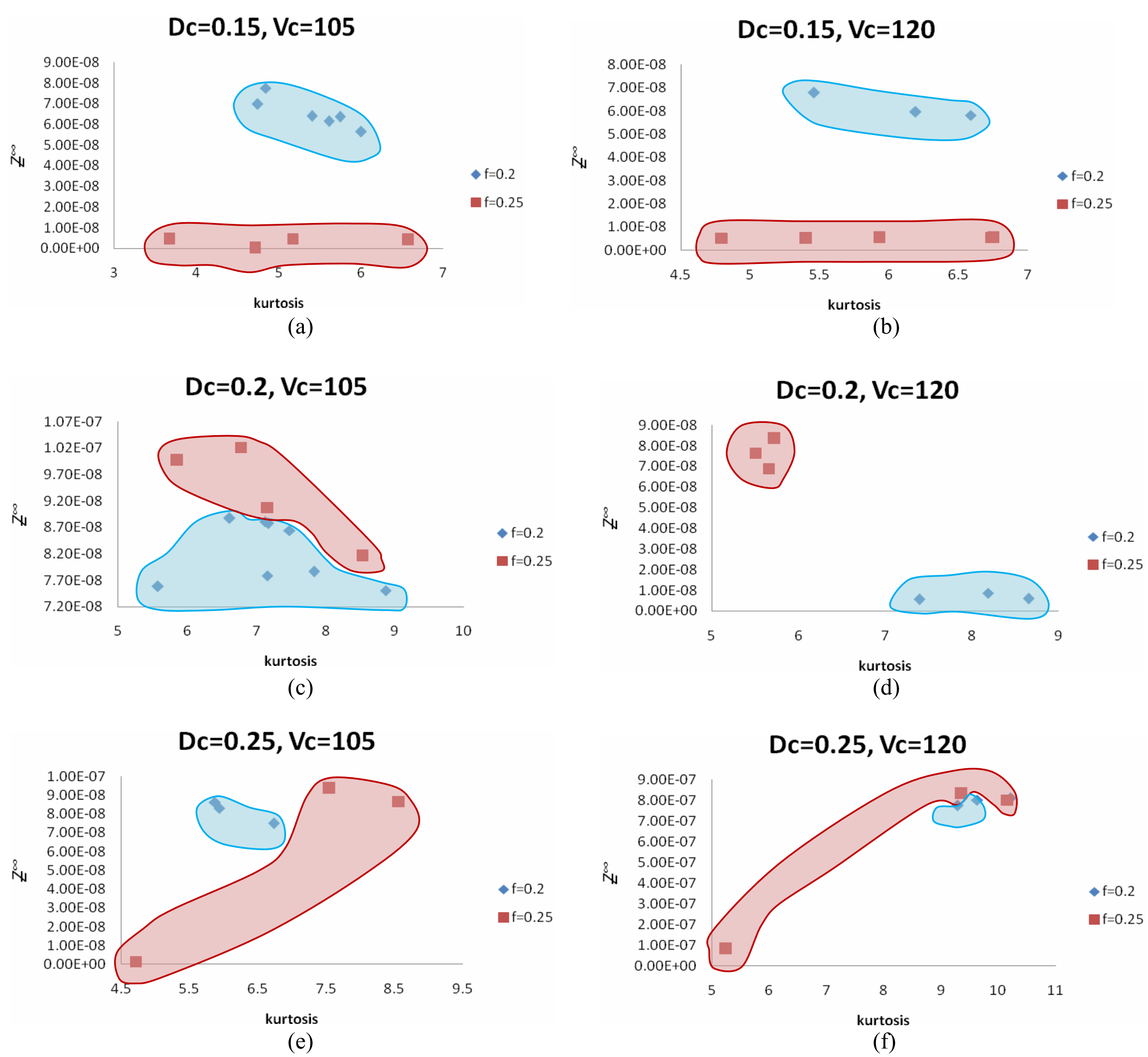


Figure 10. Signal clustering for different feed rate based on specific depth of cut, D_c and cutting speed, V_c: (a) $D_c = 0.15$, $V_c = 120$, (b) $D_c = 0.15$, $V_c = 105$, (c) $D_c = 0.2$, $V_c = 105$, (d) $D_c = 0.2$, $V_c = 120$, (e) $D_c = 0.25$, $V_c = 105$, (f) $D_c = 0.25$, $V_c = 120$

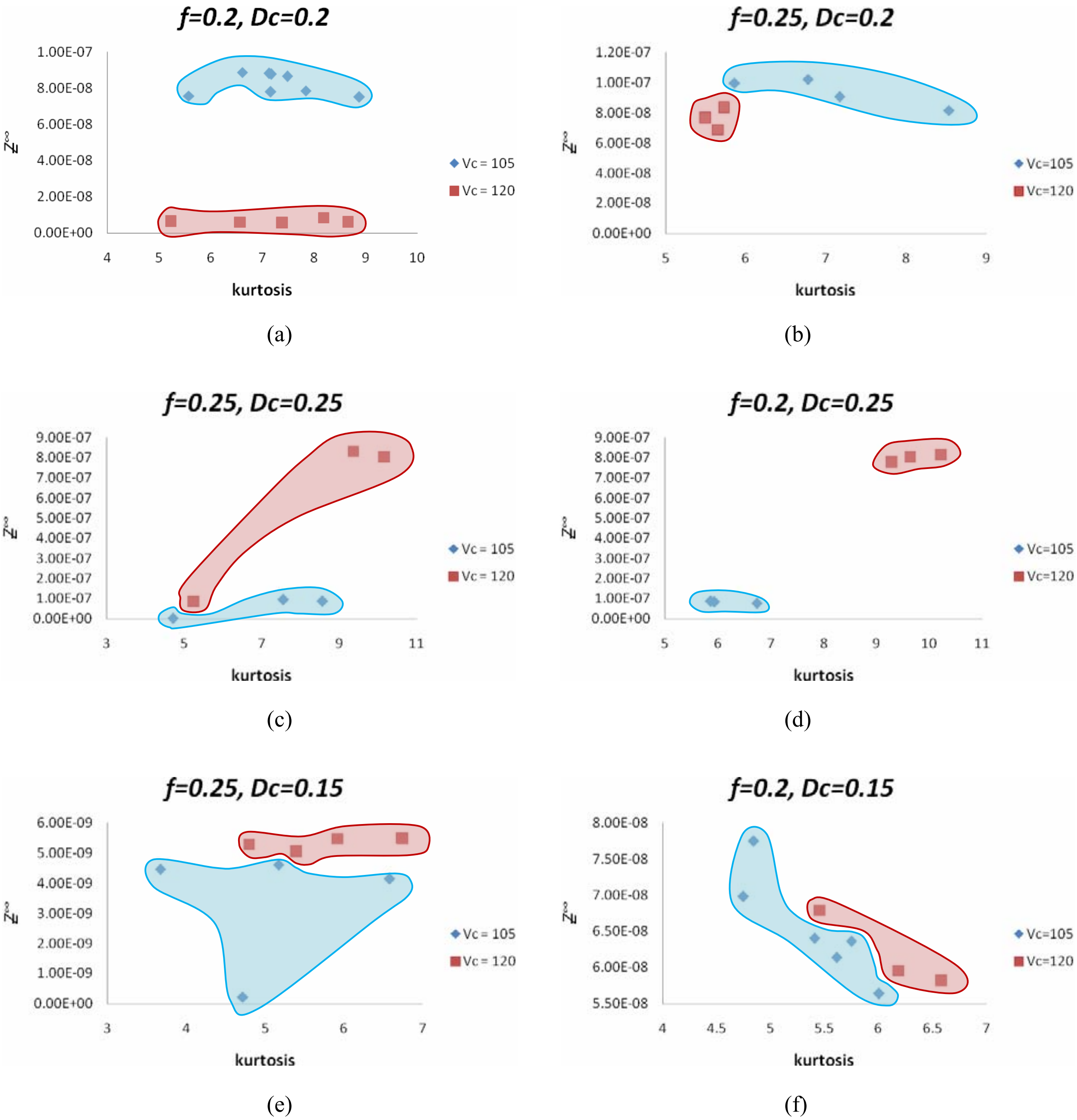


Figure 11. Signal clustering for different set of test sample based on specific cutting speed, V_c: (a) Set 1 ($f = 0.2$, $D_c = 0.2$) , (b) Set 2 ($f = 0.25$, $D_c = 0.2$), (c) Set 3 ($f = 0.25$, $D_c = 0.25$), (d) Set 4 ($f = 0.2$, $D_c = 0.25$), (e) Set 5 ($f = 0.25$, $D_c = 0.15$), (f) Set 6 ($f = 0.2$, $D_c = 0.15$)

Besides, the clustering can also be done based on the different cutting speed. This approach was capable to illustrate a more specific clustering pattern that indicates the number of test sample that being used to generate the signals. For example, Fig. 11(a) indicates a specific classification of signal for the first and the second test sample. The rest of classification illustrated in Fig. (11) indicate the other number of test sample specifically. So that, since the cutting parameter including feed rate, depth of cut and cutting speed have been initially decided, the signal conformation for the similar cutting process and cutting condition can be determined accordingly.

V. Conclusion

This paper has proven that the clustering of the machining signal can be done by plotting the statistical parameter of the measured machining signal. Utilising the newly developed statistical parameter, I-kaz coefficient, $Ƶ^{\infty}$ and the existing statistical parameter i.e. skewness and kurtosis, a significant clustering of machining signal has been obtained. This clustering approach has grouped machining signals into some unique clustering pattern. The findings of this study may very useful especially for signal conformation, where the verification of the noise nuisance to the measured signal is frequently needed. For simple cases, which only provide the feed rate information, the general classification that based on the feed rate value can be used. Otherwise, any detail analysis which considers the effect of both feed rate, depth of cut and cutting speed parameter precisely, the specific classification based on those parameters can be utilised. In addition, this kind of clustering approach obtains a more significant result where the specific number of test sample can be determined. Since the digital signal processing has become one of the most important methods to handle information, the clustering approach presented in this paper could help much in classifying machining signal especially for machining condition monitoring purpose. Thus, the reliability of the measured signal to be analysed further can be verified accordingly by observing the clustering location. In advanced, further proactive inspection can be done if there is any faulty simptomp found based on the clusters.

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