World Applied Sciences Journal 14 (10): 1541-1548, 2011
ISSN 1818-4952

Optimization of Integrated Kurtosis-Based Algorithm for Z-Filter (I-Kaz™) Coefficient Using Multi Level Signal Decomposition Technique

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Abstract: This paper presents the development of optimized Integrated Kurtosis-based Algorithm for Z-filter (I-kaz™) Coefficient using multilevel signal decomposition technique. The I-kaz™ coefficient (Z∞) was originally developed base on the 2nd order of *Daubechies* signal decomposition. Higher order of I-kaz™ coefficients, 3rd order ($^3Z^\infty$), 4th order ($^4Z^\infty$), 5th order ($^5Z^\infty$), 6th order ($^6Z^\infty$) and 7th order ($^7Z^\infty$) were investigated by analyzing their response using two types of synthetic signals, TSA and TSB. The optimized order of I-kaz Multi Level coefficient was chosen base on the sensitiveness of the coefficient response with respect to the changes of amplitude in TSA and frequency in TSB synthetic signals. This study indicated that the response of all orders of I-kaz Multi Level coefficients showed an increasing trend with respect to the increment in amplitude and frequency of TSA and TSB signals respectively. The 6th order of I-kaz coefficient, $^6Z^\infty$ was the most efficient coefficient since it showed the highest sensitivity for both types of synthetic signals. The optimized level of I-kaz coefficient $^6Z^\infty$, which is more sensitive than the current I-kaz™ coefficient Z∞ can be used for analyzing dynamic signals.

Key words: Statistical analysis · Digital signal processing · Kurtosis · Digital signal filtering

INTRODUCTION

Statistical Signal Analysis and Signal Features Extraction in Time Domain: Statistics is a mathematical science that involves data collection, analysis, interpretation and presentation [1]. Statistical analysis provides an easy and a simple analysis of a complex random signal. The main purpose of a global statistical analysis is to classify the random signal.

The classification and interpretation of the signals are to reveal the data at several levels of detail [2]. The most common parameters used in statistical analysis are the mean value, standard deviation value, the varience, the skewness, the kurtosis and the root mean square (rms) [3].

Signal features (SF) from captured signals in time domain need to be derived so that they can describe the signal adequately and maintain the relevant information [4]. Some common SFs that can be used for extraction from any time domain signal are average value, standard deviation, variance, skewness, kurtosis and root mean square (rms) [5-7].

For a signal with n-number of data points, the mean value $\bar{x}$ is mathematically defined trough equation 1.1 where x_i is the value of the data point. The mean value is one of the most important and often used parameters in indicating the tendency of the data toward the center.

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n}(x_i) \quad (1)$$

The standard deviation value is given by:

$$s = \left(\frac{1}{n}\sum_{i=1}^{n}\left(x_i - x\right)^2\right)^{\frac{1}{2}} \quad (2)$$

Where x_i is the value of the data point and $\bar{x}$ is the mean of the data. Base on equation 2, standard deviation value measures the spread of the data about the mean value. Variance is simply defined as the square of the standard deviation as shown in equation 3.

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$$\sigma = s^2 \tag{3}$$

Signal classification on the real-life signals base on mean and variance was not compatible mainly due to the signals contain outliers that can bring a noticeable shift in the actual value of both mean and variance [8].

Skewness is the measurment of the asymmetry from the normal distribution in a set of statistical data. The skewness S, of a set of data is calculated base on the equation 4.

$$S = \frac{1}{ns^3}\sum_{i=1}^{n}(x_i - \bar{x})^3 \tag{4}$$

Where x_i is the value of the data point and $\bar{x}$ is the mean of the data and s is the standard deviation value.

The signal 4th statistical moment Kurtosis K, is an important global signal statistic that is very sensitive to the spikeness of the data. The value of Kurtosis K, for descrete data sets is defined in equation 5.

$$\mathrm{K} = \frac{1}{ns^4}\sum_{i=1}^{n}(x_i - \bar{x})^4 \tag{5}$$

The kurtosis value for a normal or Gausian distribution is approximately 3.0. The presence of more extreme value or amplitude than should be found in a Gaussian distribution can be detected when the kurtosis value is higher than 3.0.

Statistical analysis using Kurtosis value were used frequently in industries in which defect synptoms can be detected due to its sensitivity towards the existence of high amplitude [8]. A propoer maintenence can be conducted systematically and accurately base on the measurment of Kurtosis value.

In engineeering statistical analysis, root-mean-square (*rms*) is the signal 2nd statistical moment and is calculated base on equation 6:

$$r.m.s. = \left(\frac{1}{n}\sum_{i=1}^{n} x_i^{\,2}\right)^{\frac{1}{2}} \tag{6}$$

Where n is the number of data and x_i is the data value.

Developement of Integrated Kurtosis-Based Algorithm (I-Kaz™): I-kaz™ was formulated base on the concept of data distribution or scattering about its centre points. It was developed with the purpose of giving descriptive and inferential statistics which is an advantage in comparison with other statistical methods that only rely on numerical value. I-kaz coefficient, Z^∞ and the value was supported by a three dimensional graphical summarisations of frequency distribution [1].

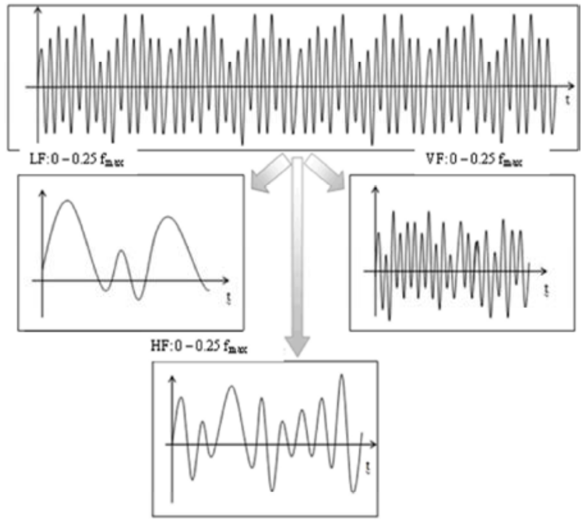


Fig. 1: The decomposition process of a signal in I-kaz procedure

Consider a typical dynamic signal as illustrated in Figure 1. The decomposition of the signal in the time domain was done by considering the 2nd order of the Daubechies concept in signal decomposition process [10].

The sampling frequency of the raw signal needs to be properly selected in order to avoid aliasing effect. Most researchers were using 2.56 Nyquist number to decide the sampling frequency. The maximum frequency span is described in equation 7.

$$f_{\max} = \frac{fs}{2.56} \tag{7}$$

For the purpose of calculation simplification, Nyquist number was chosen to be equal to 2. Figliola & Beasly also suggested that the Nyquist number must be 2 or greater than the maximum frequency in order to avoid the content of the sampling signal to be misinterpreted [10]. The decomposition of the raw signal resulted in 3 frequency ranges that were assigned to 3 different axis, x, y and z.

x-axis : Low frequency (LF) range of 0 - 0.25 f_{max}
y-axis : High frequency (HF) range of 0.25 f_{max} - 0.5 f_{max}
z-axis : Very high frequency (VF) range of 0.5 f_{max} -f_{max}

The final I-kaz coefficient Z^∞, can be simplified in K and s as shown in equation 8.

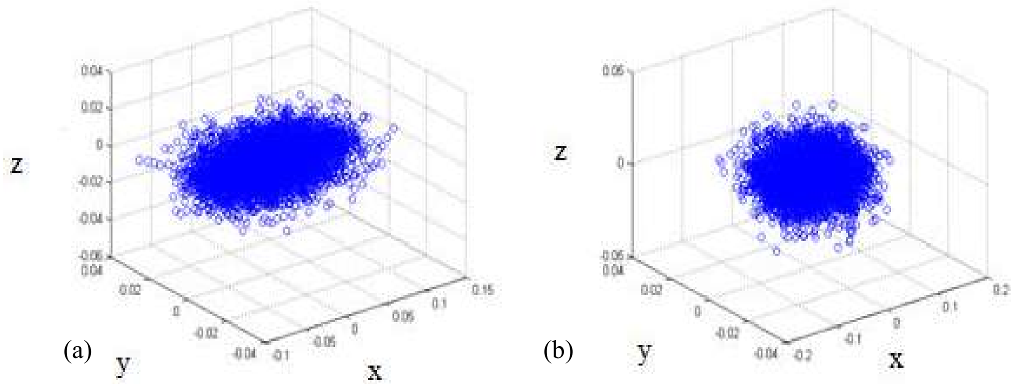


Fig. 2: I-kaz 3D graphical representation for 2 different machining acoustic signals

$$Z^{\infty} = \frac{1}{n}\sqrt{K_L s_L^4 + K_H s_H^4 + K_V s_V^4} \quad (8)$$

Where K_L, K_H, K_V, s_L, s_H dan s_V are the kurtosis and the standard deviation for LF, HF and VF frequency range respectively. Figure 2 shows the 3D graphical representation of I-kaz for 2 different machining acoustic signals.

In previous researches, I-kaz coefficient was used as the parameter to translate the signals features. J.A. Ghani in her study used the I-kaz coefficient to analyze the flank wear during turning process for tool wear prediction purpose [12]. Nuawi in his study used I-kaz for the correlation of structure-borne sound signal and internal piping surface condition. The structure-borne sound signal analyzed using I-kaz which correlated with the internal pipe surface condition showed high ability to differentiate between the smooth and rough pipe surface [13]. Another study showed that the I-kaz method was capable of improving the Taylor curve which was unable to exhibit the three typical wear curve for the cutting that use certain cutting speed [14].

Developement of I-Kaz™ Multi Level Coefficient ($^LZ\infty$): The development of I-kaz™ Multi Level coefficient ($^LZ\infty$) was inspired by the original I-kaz ($Z\infty$) which was pioneered by M.Z. Nuawi [1]. The new symbol for I-kaz Multi Level coefficient is defined as $^LZ\infty$ in which L is referring to the number of order of signal decomposition. The decomposition of signals in time domain into more frequency bands is to get a better time resolution [3]. The new developed coefficient ($^LZ\infty$) is expected to have more sensitivity towards amplitude and frequency change in a signal. In I-kaz Multi Level method, signal decomposition using n^{th} order of Daubechies theorem will result in $n+1$ number of frequency bands. This algorithm was summarized as presented in Figure 3.

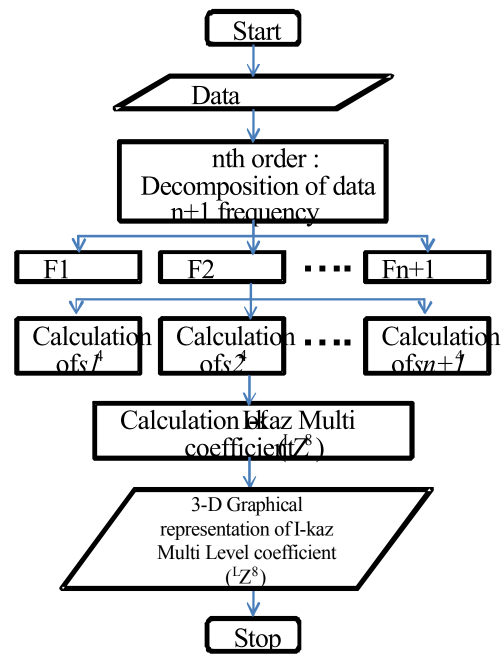


Fig. 3: Flowchart of the I-kaz Multi Level method

The frequency range of F_1, F_2, F_3 to F_n in Fig 3 are depending on the value of n and f_{max}. For I-kaz™ Multi Level with n^{th} order of signal decomposition and for $i = 1, 2, 3....n+1$, the frequency ranges are shown below:

$F_{i=1}$: $F_{i=1\ min} = 0$ and $F_{i=1\ max} = 0.5f_{max} / (2^{\ n-1})$ (10)

$F_{i=2}$: $F_{i=2\ min} = F_{i=1\ max}$ and $F_{i=2\ max} = 0.5f_{max} / (2^{\ n-2})$ (11)

$F_{i=n+1}$: $F_{i=n+1\ min} = F_{i=n\ max}$ and $F_{i=n+1\ max} = 0.5f_{max} / (2^{\ n-(n+1)})$ (12)

The related multi I-kaz coefficient can be calculated as:

$$^{L}Z^{\infty} = \frac{1}{n}\sqrt{K_1 s_1 + K_2 s_2 + K_3 s_3 ... + K_{n+1} s_{n+1}} \quad (13)$$

Where L = n and it indicates the order of signal decomposition.

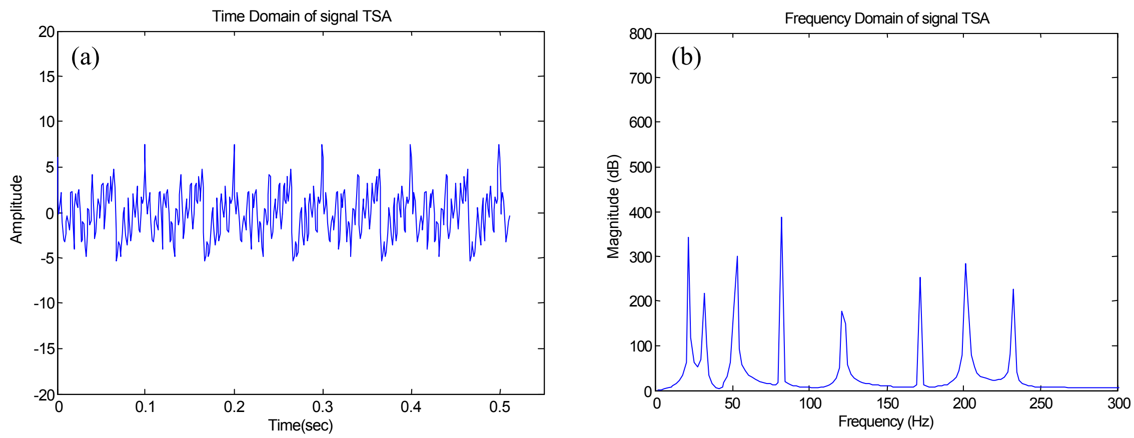


Fig. 4(a): Time domain of signal TSA
Fig. 4(b): Frequency domain of signal TSA

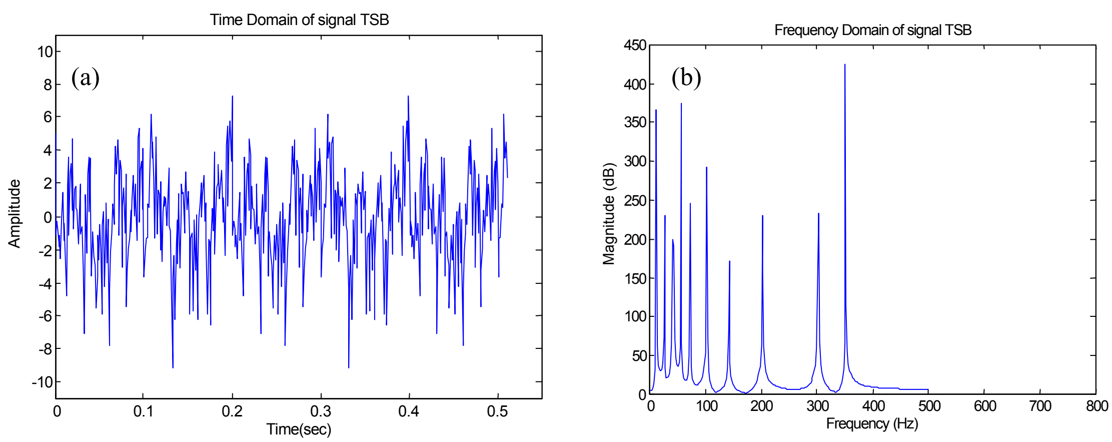


Fig. 5(a): Time domain of signal TSB
Fig. 5(b): Frequency domain of signal TSB

MATERIALS AND METHODS

Creating Synthetic Signals: Two types of synthetic signals, TSA and TSB were created with different specifications. Both signals were created by using MATLAB programming and were defined with 512 data points and sampled at 1000 Hz (F_s = 1000 Hz). The TSA synthetic signal consists of 20, 30, 50, 80, 120, 170, 200 and 230 Hz sinusoidal waves while the TSB synthetic signal consists of 10, 25, 40, 55, 70, 100, 140, 200, 300 and 450 Hz sinusoidal waves. The plot of TSA and TSB in time and frequency domain were shown in Figure 4 and Figure 5.

Signal with Different Amplitude with Constant Frequency: TSA signal will be used to study the respond for each coefficient toward amplitude change in a signal. The amplitude of signal TSA was increased by the increamental of 10% while the frequencies were kept constatnt. For each amplitude increment, the higher order of I-kaz coefficients, $^3Z^\infty$, $^4Z^\infty$, $^5Z^\infty$, $^6Z^\infty$ and $^7Z^\infty$ and also the current statistical coefficients, kurtosis (K), standard deviation (s), RMS and skewness (S) were calculated and compared.

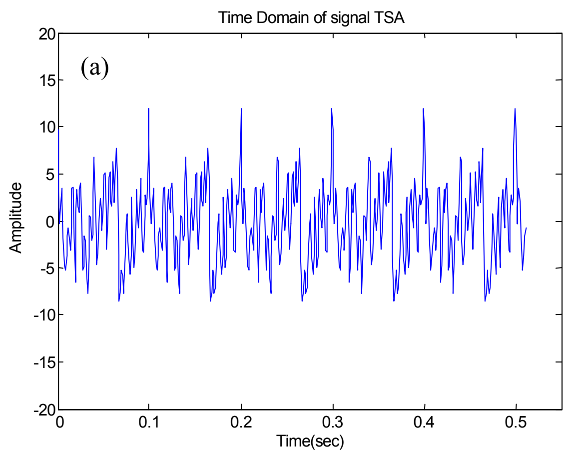
Signal with Different Frequency with Constant Amplitude: TSB signal will be used to study the respond for each coefficient toward frequency change in a signal. The frequency of signal TSB was increased by the increamental of 10% while the amplitude were kept constatnt. Similarly, for each frequency increment, the higher order of I-kaz coefficients, $^3Z^\infty$, $^4Z^\infty$, $^5Z^\infty$, $^6Z^\infty$ and $^7Z^\infty$ and also the current statistical coefficients, kurtosis (K), standard deviation (s), RMS and skewness (S) were calculated and compared.

RESULT AND DISCUSSION

I-Kaz Multi Level Coefficient Response Towards the Amplitude Change of TSA Signal: Six types of signals from original TSA signal were created by inceasing its amplitude from 10% to 60% by 10% increamental. Figure 6(a) and 6(b) show the sample plot of TSA signal in time and frequency domain after 60% amplitude increment.

The result of kurtosis (K), standard deviation(s), rms, skewness (S), I-kaz (Z^{∞}) and I-kaz Multi Level coefficients (${}^{L}Z^{\infty}$) toward different level of amplitude for the TSA signal are presented in Table 1.

The sensitivity of all coefficieents toward the amplitude change can be seen clearly from Table 2. I-kaz series of coefficients were seen to be much more sensitive as compared to standard deviation (s) and RMS. The higher the order of the I-kaz Multi Level coefficients, the more sensitive it responded to the amplitude change. For this type of particular synthetic signal, the sensitivity of the I-kaz Multi Level coefficient saturated at the 5th order (${}^{5}Z^{\infty}$).



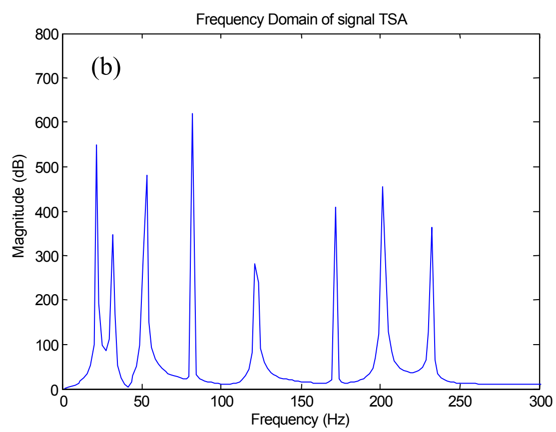


Fig. 6(a): 60% increase in time domain
Fig. 6(b): 60% increase in frequency domain

Table 1: The respond of each coefficient in deviation percentage with respect to TSA signal

TSA %	10%	20%	30%	40%	50%	60%
Z^{∞}	21.4286	44.1558	69.4805	96.1039	125.3247	156.4935
${}^{3}Z^{\infty}$	20.3540	43.3628	68.1416	95.5752	123.8938	154.8673
${}^{4}Z^{\infty}$	20.2247	43.8202	68.5393	95.5056	124.7191	155.0562
${}^{5}Z^{\infty}$	21.5909	44.3182	69.3182	96.5909	125.0000	156.8182
${}^{6}Z^{\infty}$	21.5909	44.3182	69.3182	96.5909	125.0000	156.8182
${}^{7}Z^{\infty}$	21.5909	44.3182	69.3182	96.5909	125.0000	156.8182
Kurtosis	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Skewness	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Std-Dev	9.9980	20.0000	29.9980	40.0000	49.9980	60.0000
RMS	10.0087	20.0173	30.0087	40.0173	50.0087	60.0173

Table 2: The response of each coefficient in deviation percentage for TSB signal

TSB %	10%	20%	30%	40%
Z^{∞}	1.2579	0.6289	1.8868	2.5157
${}^{3}Z^{\infty}$	0.8264	4.1322	1.6529	0.8264
${}^{4}Z^{\infty}$	3.7736	8.4906	7.5472	9.4340
${}^{5}Z^{\infty}$	5.0000	10.0000	11.0000	13.0000
${}^{6}Z^{\infty}$	6.0606	11.1111	12.1212	14.1414
${}^{7}Z^{\infty}$	6.0606	11.1111	12.1212	14.1414
Kurtosis	3.3836	0.1983	1.2983	0.2975
Std-Dev	0.1556	0.2687	0.3217	0.1591
RMS	0.1720	0.2659	0.3441	0.1564

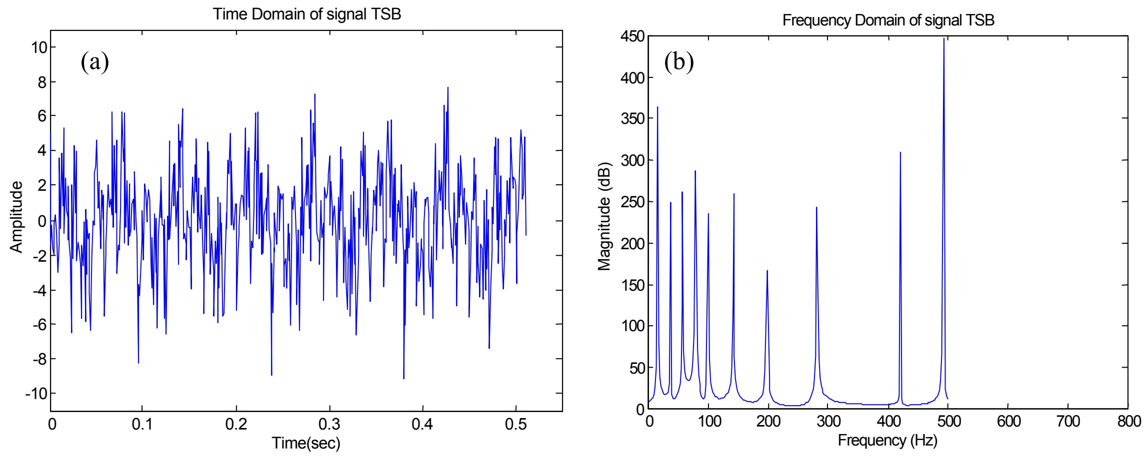


Fig. 7(a): 40% increase in time domain

Fig. 7(b): 40% increase in frequency domain

I-Kaz Multi Level Coefficient Response Toward Frequency Change of TSB Signal: Four types of signals from original TSB signal were created by inceasing its sinusoidal frequency by 10% incremental. Figure 7(a) and 7(b) show the sample plot of TSB signal in time and frequency domain after 40% frequency increment of original TSB signal.

The result of kurtosis (K), standard deviation(s), RMS, skewness (S), I-kaz (Z^∞) and I-kaz Multi Level coefficients (${}^{L}Z^\infty$) toward different degree of sinusoidal frequencies for the TSB signal are presented in Table 2.

The sensitivity of all coefficieents toward the frequency change can be seen clearly from Table 4. Similarly in TSA signal study, the I-kaz series of coefficients were seen to be much more sensitive than other coefficients. The higher the order of the Multi I-kaz coefficients, the more sensitive it responded to the frequency change. For this type of particular synthetic signal, the sensitivity of the Multi I-kaz coefficient saturated at the 6^{th} order (${}^{6}Z^\infty$). The sensitivity of I-kaz coefficient towards frequency change was proven in the study of condition-based monitoring on automotive gearbox using ultrasonic signal in which I-kaz coefficient was used in clustering process against Kurtosis, Crest Factor and Skewness [15].

I-Kaz Multi Level Representation for TSA and TSB Signals: The original I-kaz™ technique provide one 3-D graphical illustration. The new I-kaz Multi Level provides a better illustarion since it generates two 3-D graphical representations that separate low level and high level frequency bands. The higher value of ${}^{6}Z^\infty$ refers to the bigger space scattering of I-kaz Multi Level representation and the significance of the scattering could be identified to be at the lower or higher frequency band.

By using equation 7, for the Nyquist number equal to 2, frequency span equal to 1000Hz, f_{max} equal to 500 Hz and L is equal to 6, the frequency ranges of the Lower Frequency Band and the Higher Frequency Band of the I-kaz Multi Level representation can be summarized as follows:

Lower Frequency Band:

- X - axis: 0.00 Hz to 15.60 Hz
- Y - axis: 15.60 Hz to 31.25 Hz
- Z - axis: 31.25 Hz to 62.50 Hz

Higher Frequency Band:

- X - axis: 62.50 Hz to 125.00 Hz
- Y - axis: 125.00 Hz to 250.00 Hz
- Z-H axis: 250.00 Hz to 500.00 Hz

The dual 3-D Multi I-kaz representation are shown in Figure 8 and 9 for the original TSA signal and the TSA signal after 60% increase respectively.

Lower Frequency Band Higher Frequency Band: A similar I-kaz 3D scattering pattern was reported by Nuawi M.Z. when studying for the filtered and the unfiltered signal in machining. The data distribution of the I-kaz representation for the Z-notch filtered signal was shrunk compared to the unfiltered signal [16].

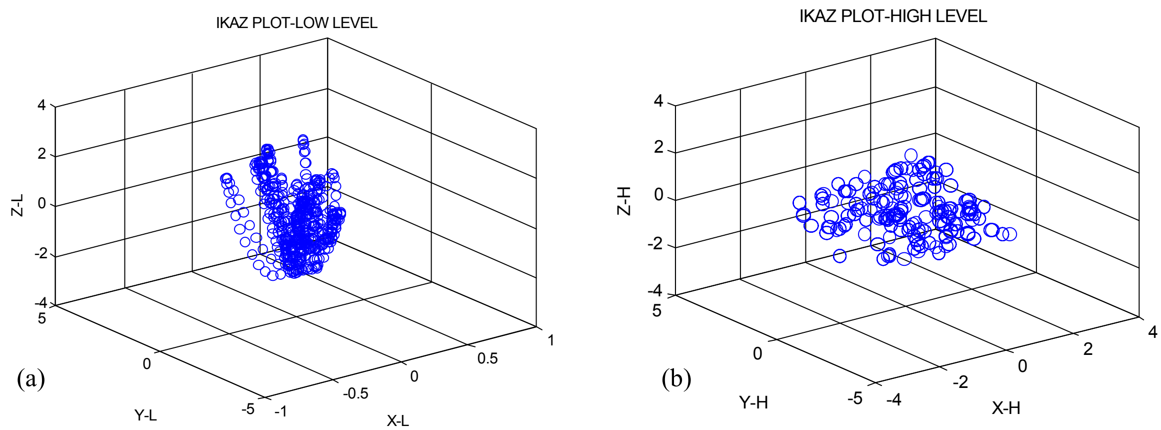


Fig. 8(a): TSA Lower Frequency Band
Fig. 8(b): TSA Higher Frequency Band

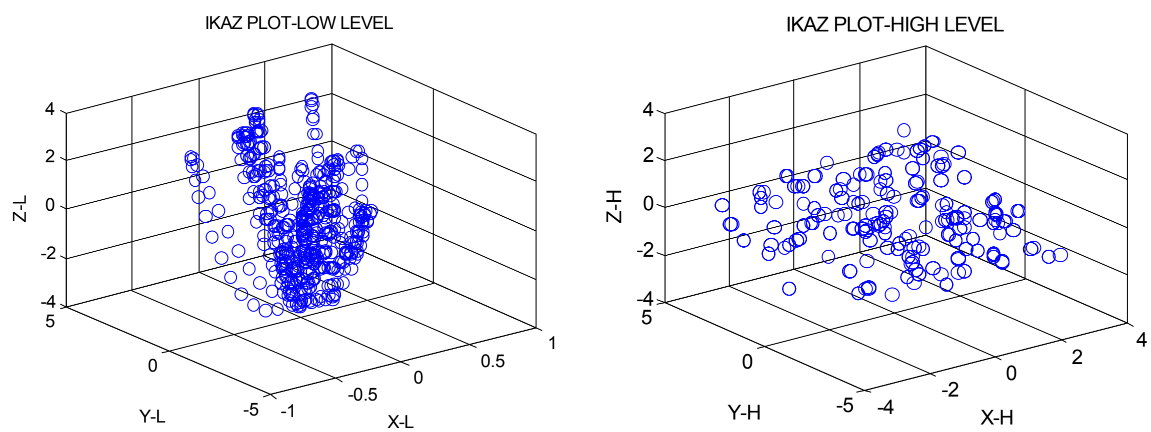


Fig. 9(a): TSA 60% increased
Fig. 9(b): TSA 60% increased

CONCLUSION

This study discussed the development of an alternative statistical analysis method, known as I-kaz Multi Level. This method was originally developed base on I-kaz^{TM} but with higer order of signal decomposition. This new I-kaz Multi Level method was proven to be very sensitive and detects very well in amplitude and frequency changes of a measured signal. The I-kaz Multi Level coefficient ($^{L}Z\infty$) response was much better toward amplitude and frequency changes as compared to $Z\infty$ coefficient and to current statistical coefficients; kurtosis (K), standard deviation (s), Skewness (S) and RMS.

In TSA signal study, the value and the sensitivity of I-kaz Multi Level coefficient ($^{L}Z\infty$) toward the amplitude change was higher at a higher order of signal decomposition. The sensitivity of $^{5}Z\infty$, $^{6}Z\infty$ and $^{7}Z\infty$ were at 21.5909%, 44.3182%, 69.3182%, 96.9509%, 125.0000% and 156.8182% for 10%, 20%, 30%, 40%, 50% and 60% of TSA amplitude increments respectively. It could therefore be inferred that higher order of I-kaz Multi Level coefficient would be more sensitive toward amplitude change in a measured signals and it saturated at 5th order ($^{5}Z\infty$).

For the second study of TSB signal, a similar condition was observed. The value and sensitivity of I-kaz Multi Level coefficient was higher at a higher order of signal decomposition. The sensitivity of $^{6}Z\infty$ and $^{7}Z\infty$ were at 6.0606, 11.1111, 12.1212 and 14.1414 for 10%, 20%, 30% and 60% of TSB sinusoidal frequency increments respectively. Therefore, it can be concluded that the higher order of I-kaz Multi Level coefficient, the more sensitive it responded toward the frequency change in a measured signals and it saturated at 6th order ($^{6}Z\infty$).

Considering both studies of TSA and TSB signals, the most efficient I-kaz Multi Level coeffieicnet to be used was coefficient at 6th order, which is $^{6}Z^{\infty}$. The higher value of $^{6}Z^{\infty}$ coefficient indicates the present of higher amplitude and frequency in a signal which can be simultaneously monitored using the I-kaz Multi Level representation. By observing the space of scattering at the Lower Band Frequency and the Higher Band Frequency, the bigger space of scattering indicates that the frequency or the amplitude of the signal is comparatively going higher. This optimized I-kaz Multi Level coefficient is very sensitive and reliable especially for monitoring purpose or analyzing dynamic signals in which the observations of amplitude and frequency changes in measured signals are very important and critical.

ACKNOWLEDGEMENT

The authors wish to express their gratitute to Universiti Kebangsaan Malaysia and Ministry of Science, Technology and Innovation, through the fund of 03-01-02-SF0647, for supporting this research.

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