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Kurtosis Based Time-frequency Analysis Scheme for Stationary or Non-stationary Signals with Transients

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Abstract: This study presented an efficient time-frequency analysis scheme for vibration signals with transients. The scheme was developed based on the short-time Fourier transform with varying window size over time. The variable window size was determined by the local kurtosis. In regions where the kurtosis measured relatively high, a large window size was applied to improve the resolution of time-frequency image. Conversely, a small window size was applied to regions where the kurtosis measured relatively low. The method was tested by simulation signals and vibration signals in SNR 10 dB Gaussian noise. The results showed that the stationary or non-stationary signals with transients can be retrieved in time-frequency image.

Key words: Kurtosis, condition monitoring, time-frequency analysis, vibration signals with transients

INTRODUCTION

The time series and the spectrum of signals are the most important and fundamental indexes in machinery condition monitoring. For non-stationary signals or signal with transients, the time domain or frequency domain analysis loses faults detection in many rotating machines. The Short-time Fourier transform (STFT) is the most widely tool for the display non-stationary signals in time-frequency domain. However, the STFT cannot obtain a good resolution image simultaneously in both time and frequency domains. There exists a fundamental resolution tradeoff: improving the frequency resolution (by using a large window size) results in a loss of time resolution or improving the time resolution (by using a small window size) results in a loss of frequency resolution (Cohen, 1989; Hammond and White, 1996; Sejdic *et al*., 2009). Thus, looking for a variable window size scheme for STFT is of great worth.

Recent study have been developed the signal dependent adaptive time-frequency analysis, in which the algorithm is allowed to adapt based on optimized performance (Jones and Baraniuk, 1994; Czerwinski and Jones, 1997; Liu *et al*., 2007; Zhong and Huang, 2010). But these methods often require either computationally expensive or perform only off-line applications. For the purpose of on-line applications, an efficient Variable Short-time Fourier Transform (VSTFT) is proposed in this study. The VSTFT is a data dependent algorithm, where the local window size is allowed to change based on a single parameter of the kurtosis (Wiggins, 1978; Lee and Nandi, 2000). It is a low computing cost scheme.

VARIABLE STFT SCHEME

The basic ideal of short-time Fourier transform is that if one wants to know what frequencies exist at a particular time. Then take a small part of the signal around that time and Fourier analyzes it, neglecting the rest of signal. Since the time interval is short compared to the whole signal, this process is called taking the short-time Fourier transform. For a given signal x(t), the STFT is:

$$STFT(t_{fix}, f) = \int_{-\infty}^{\infty} x(\tau) w^*(\tau - t_{fix}) e^{-j2\pi f\tau} d\tau \qquad (1)$$

$$t_{fix} = t_s (N_{fix}) \qquad (2)$$

where, w(t) is a Gaussian window function (Lee, 2010), * is a complex conjugate, t_s is sampling time, N_{fix} is a fixed window size, t_{fix} is a fixed time delay and f is frequency.

The proposed scheme is data dependent and requires a measurement of the local kurtosis that is similar to the high order statistics used for deconvolution in signal processing (Lee and Nandi, 2000). The local short-time time-frequency kurtosis is defined as:

$$K_{local} = \frac{\int_{-\infty}^{\infty} |STFT(t_{fix}, f)|^4 df}{\left(\int_{-\infty}^{\infty} |STFT(t_{fix}, f)|^2 df\right)^2} \qquad (3)$$

Compared to the STFT of Eq. 1, the proposed variable STFT scheme measured the local kurtosis K_{local} for windowed data over time and the local window size is determined by:

$$N_{local} = N_{max}\frac{K_{local}}{K_{max}} \quad (4)$$

where, K_{local} is a maximum kurtosis for all K_{local} and N_{max} is a pre-set maximum variable window size. Thus, the local window size N_{local} is proportional to the value of the local kurtosis K_{local}. For a given signal x(t), the variable STFT is:

$$VSTFT(t_{local}, f) = \int_{-\infty}^{\infty} x(\tau)w^*(\tau - t_{local})e^{-j2\pi f\tau}d\tau, \quad (5)$$

$$t_{local} = t_s\,(N_{local}) \quad (6)$$

where, t_{local} is a local time delay. With this procedure, the time and frequency resolutions are linked to the kurtosis. In regions where the kurtosis measures relatively high, a large window size is applied to improve the resolution of time-frequency image. Conversely, a small window size is applied to regions where the kurtosis measures relatively low. The kurtosis based variable STFT algorithm is as follows.

```
Algorithm: Kurtosis based variable STFT
Initialization:
Set N_fix = N_Max as a fixed window size for STFT.
Fori Loop = 1:SignalLength
        Calculate the local kurtosis K_local for every windowed data in Eq. 3
End
Find K_Max from for all K_local.
Variable STFT:
Set N_max as a maximum window size for variable STFT.
Fori Loop = 1: SignalLength
        Determine the local variable window size N_locla using Eq. 4.
        Calculate the STFT with variable window size using Eq. 5.
End
Plot time-frequency contour plot
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Finding an optimal window size solution for an adaptive scheme could require excessive computation power, yet still obtain an insignificant result. By using the proposed VSTFT scheme, the local variable window size is obtained using a simple and time-efficient algorithm without any optimization procedures. Thus, the computing cost of the VSTFT algorithm is only slightly greater than that of the standard STFT.

SIMULATION RESULT AND DISCUSSION

The simulation signals shown in Fig. 1a contain three types of signals: three impulses appear at 0.1, 0.2 and 0.9 sec; mixed sinusoids (0.5 sin $(2\pi f_1 t$+0.5 sin $(2\pi f_2 t))$, where f_1 = 100 and f_2 = Hz) appear between 0.4 and 0.5 sec; mixed chirp signals (sin $[2\pi(f_3 t+f_3 t)]$+sin (sin $[2\pi(f_4 t+f_4 t)]$ here f_3 = 50 and f_3 = 100 Hz) appear between 0.7 and 0.8 sec. The signal is sampling at 1 kHz and the Gaussian noise SNR 10 dB is added to the data. The corresponding frequency spectrum is shown in Fig. 1b.

Figure 2a shows the time-frequency contour plot using the STFT scheme, where the fixed Gaussian window size is N_{fix} = 128. The STFT scheme smears the impulse components in the time domain, although it detects the sinusoidal components in the frequency domain. Figure 2b shows the time-frequency contour plot using window size N_{fix} = 64, where the impulse components match in the time domain, although the sinusoidal components smear in the frequency domain. These results demonstrate the discussed tradeoff of the STFT scheme. It is impossible to obtain good time and good frequency resolutions simultaneously when using a fixed window size only.

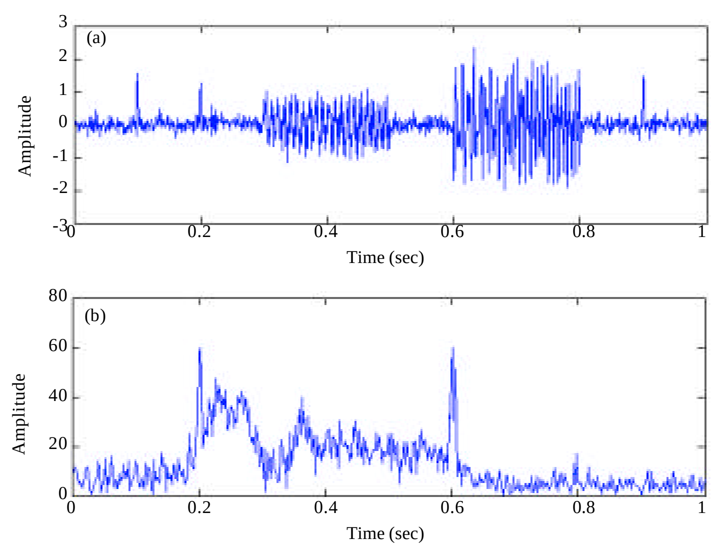

Fig. 1(a-b): Simulation signals with additive SNR 10 dB Gaussian noise (a) Time series and (b) Frequency spectrum

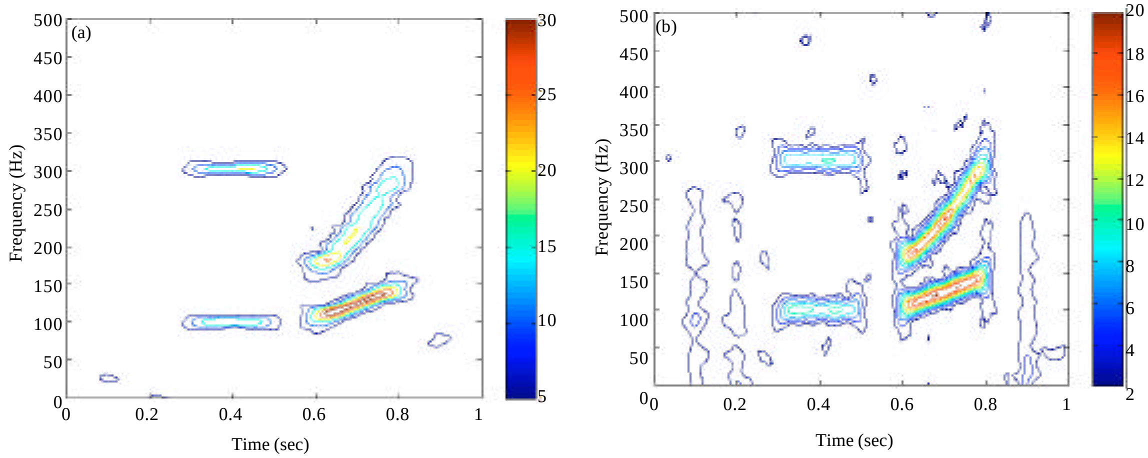

Fig. 2(a-b): Time-frequency contour plot using Fig. 1 data and STFT with fixed window size (a) N_{fix} = 128 and (b) N_{fix} = 64

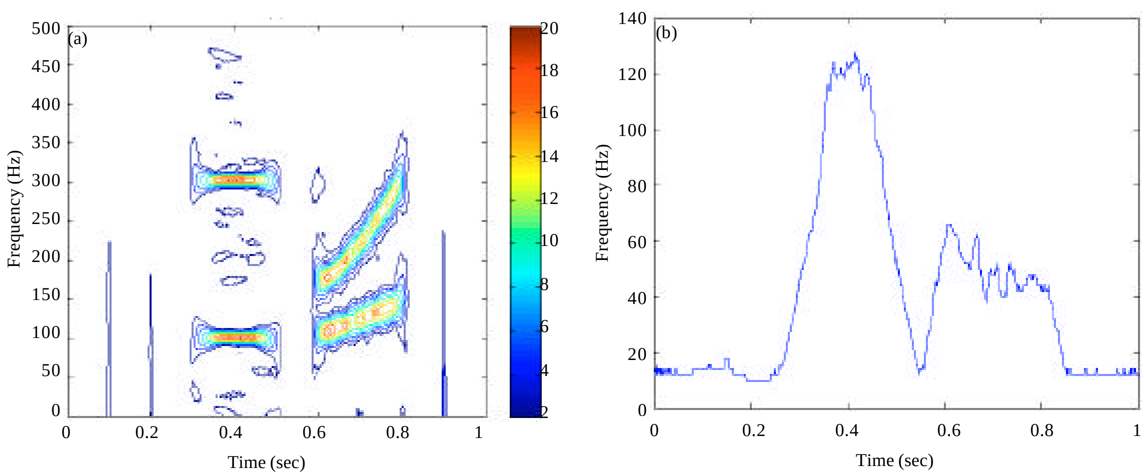

Fig. 3(a-b): Using VSTFT with N_{max} = 128 and Fig. 1 data (a) Time-frequency contour plot and (b) Adaptive window size along the time axis

Using the proposed VSTFT scheme, Fig. 3 shows the time-frequency contour plot where a dynamic Gaussian window size is based on the variations of the local kurtosis. Figure 3a shows distinguishable stationary components with transients in time and frequency domains. The variable window size is a function of time, as shown in Fig. 3b. Compared to the time-frequency contour plot using the STFT scheme in Fig. 2, the VSTFT scheme can properly select window sizes for distinguishing between harmonics and transients. This also demonstrates the VSTFT scheme is robust for Gaussian noise.

RESULTS AND DISCUSSION

In this section, the experimental vibration signals from a rotating generator are measured, as shown in Fig. 4. The National Instruments NI 9234 dynamic signal acquisition module and integrated circuit piezoelectric accelerometer (100 mV g^{-1}) are applied for signal measurement. Figure 5a shows the time series of the vibration signals at sampling rate 20 kHz. The corresponding frequency spectrum is shown in Fig. 5b. The signals contain the main steady-state sinusoids signal at 6.5 k Hz and the unknown transients caused by coupling faults between two motors.

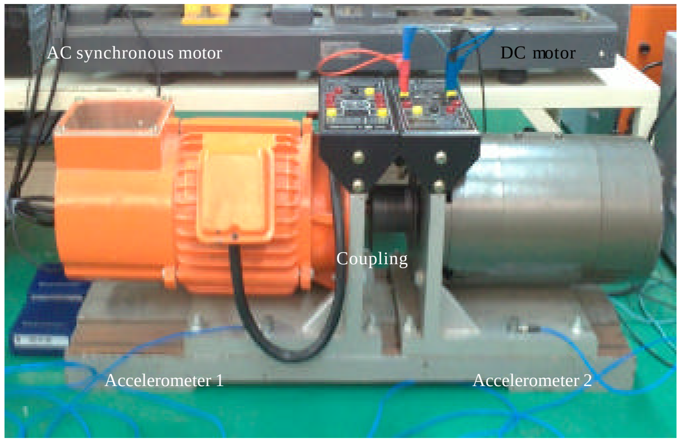

Fig. 4: Experimental setup

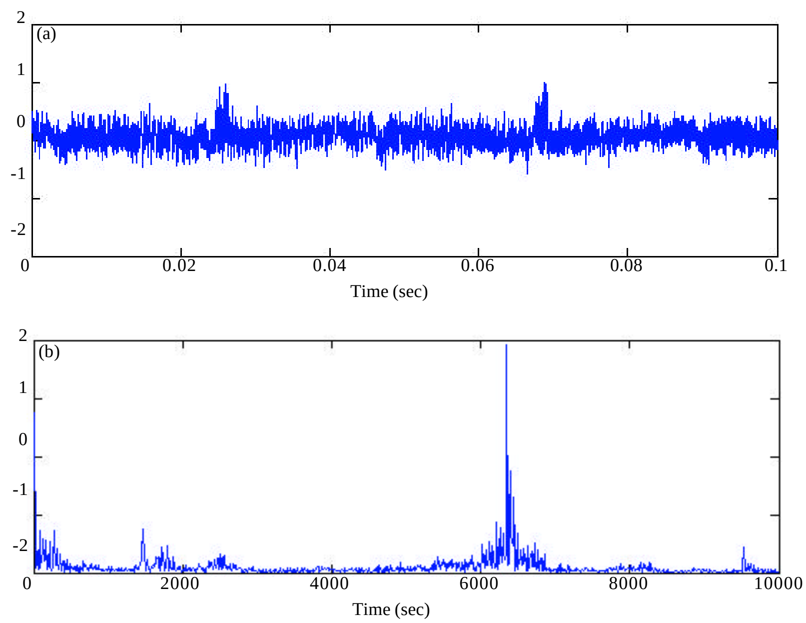

Fig. 5(a -b): Rotating vibration signals (a) Time series and (b) Frequency spectrum

Figure 6a shows the time-frequency contour plot using the STFT scheme, where the fixed Gaussian window size is N_{fix}= 128. The result shows the transients signal, appear around 0.01, 0.03, 0.05, 0.07 and 0.09 sec. It is not clear enough for impacting detection. Figure 6b shows the results of setting N_{fix} = 64 to improve the time resolution while the frequency resolution is reduced because of the short window size. When the proposed VSTFT scheme is applied, Fig. 6c shows a time-frequency contour plot with maximum window size N_{fix} = 128. The stationary components and transient signals are retrieved successfully. This confirms that the dynamic kurtosis measurement is suitably designed for the adaptive scheme, where the window size changes dynamically in conjunction variations in the vibration signals.

Figure 7 shows the time-frequency plots using the measured signals of Fig. 5 with additive SNR 10 dB Gaussian noise. Figure 7a shows the time-frequency contour plot using the STFT scheme with N_{fix} = 64, where the transient signals are smeared by noise. Using the VSTFT scheme the result shown in Fig. 7b, the harmonic

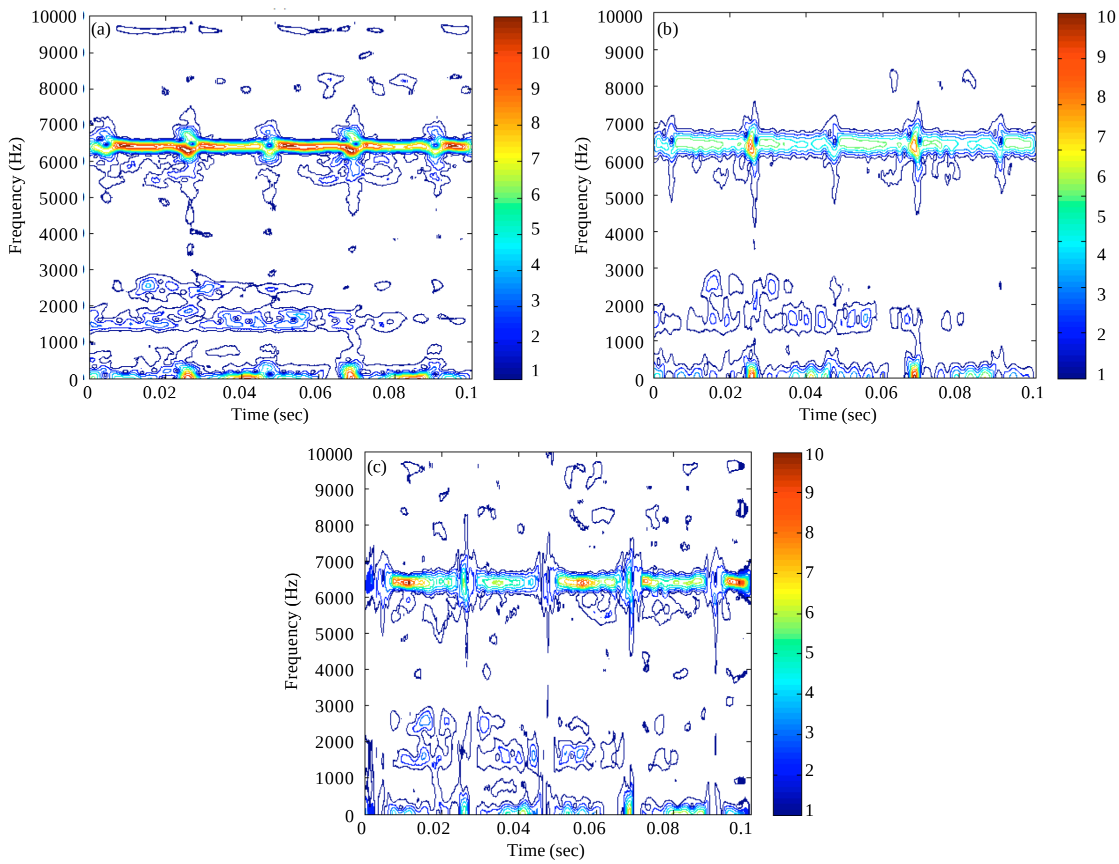

Fig. 6(a-c): Time-frequency contour plot using Fig. 5 data (a) STFT with $K_{max} = 128$, (b) STFT with $k_{locla} = 64$ and (c) VSTFT with $N_{max} = 128$

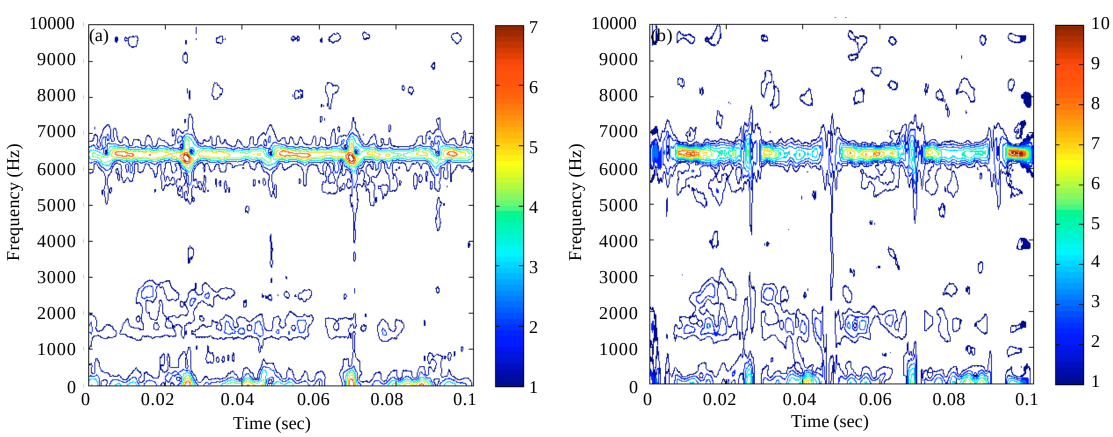

Fig. 7(a-b): Time-frequency contour plots of Fig. 5 data with 10 dB Gaussian noise (a) STFT with $N_{fix} = 64$ and (b) VSTFT with $N_{max} = 128$

signals with transients are retrieved successfully. This confirms the VSTFT scheme is robust for measurement noise.

CONCLUSION

In this study, an efficient variable time-frequency analysis scheme is proposed. The algorithm varies the window size along the time axis based on the measurement of the local kurtosis. The method is tested using simulation signals and vibration signals. The results show that it is suitable for dealing with vibration signals with transients. Under the noise condition SNR 10 dB, the results show a better performance than the standard STFT and the computational cost is only slightly greater than that of the standard STFT scheme.

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