Title: **Comparison of Short-time Fourier Transform and Wavelet Transform of Transient and Tone Burst Wave Propagation Signals For Structural Health Monitoring.**

Author**:** Victor Giurgiutiu[1]
Lingyu Yu[2]

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Abstract[1]

Advanced signal processing approaches are widely used for nondestructive evaluation, structural health monitoring and damage detection. In this research, signals related to damage in a thin plate specimen were collected by piezoelectric wafer active sensors. Damage is detected and evaluated by using advanced signal processing approaches, including the short-time Fourier transform and the wavelet transform for the two dimensional time-frequency analysis. In addition, a denoising process is included before the signal analysis to improve the detectability. Advantages and disadvantages of each approach are investigated based on the results of simulation. Comparisons are concluded at the end of this paper.

1. Introduction

Damage detection can be used to monitor the system performance, detect damage occurrence and give prognosis or diagnosis, by which the operators can make corresponding maintenance and repair decisions. Typically, damage detection consists of two parts: first, a sensing system to collect the signals related to system performance; second, a signal processing and analysis algorithm to interpret the signals. According to Staszewski (2002), many of the advances in damage detection are related to the development of signal processing techniques. The objectives of signal analysis for damage detection, nondestructive evaluation (NDE), and structural health monitoring (SHM) is to eliminate or reduce the noise in the original signals, to analyze the frequency composition, and to evaluate the damage if it occurs. In damage detection, signal analysis is used to extract changes in a signal related to damage and then characterize the changes. Hence, there are two things that need to be considered: determining which signals to measure for monitoring, and choosing efficient signal analysis approaches to best interpret the measurements. Considering the disturbance coming from the environment and the measuring process, it is necessary to erase or reduce the disturbance before signal analysis. Most practical signals in engineering are non-stationary signals, whose

[1] Graduate Research Assistant, Department of Mechanical Engineering, University of South Carolina, Columbia, SC 29208, yu3@engr.sc.edu; 803-777-8018.

[2] Graduate Research Assistant, Department of Mechanical Engineering, University of South Carolina, Columbia, SC 29208, yu3@engr.sc.edu; 803-777-1535.

frequencies evolve with time. However, the traditional frequency analysis method, the Fourier transform can only be applied to stationary signal, whose frequencies keep constant. It cannot explicitly indicate the evolution of frequencies over time. Therefore, other methods are required for non-stationary signal analysis.

The object of our research is a thin-plate specimen. An array of eleven piezoelectric wafer active sensor (PWAS) is used to detect the damage occurring in the far field of the sensors. One sensor excites wave propagation in the structure and the other sensors detect the responses. Figure 1 shows a set of signals collected during the experiment. Sensor #11 sends out a tone-burst Lamb wave with constant amplitude to excite wave propagation. The first wave packages in signals are the excitation echoes, and the other packages are echoes from the free boundary or the damage. All these signals are non-stationary. We need to identify those echoes caused by damage. Damage in the system will show up as new frequency components or result in new frequency distribution in the spectrum. The objective in our research is to generate spectrum in terms of both time and frequency showing the frequency evolution over time, or roughly locate frequency changes. According to this objective, time-frequency analysis methods are used. The two methods being used are short-time Fourier transform (STFT) and wavelet transform (WT). STFT is a modified conventional Fourier transform so that it has a direct connection to the Fourier transform, making it easy to apply and understand. WT is used first as an improvement over STFT, but also as a comparison to it.

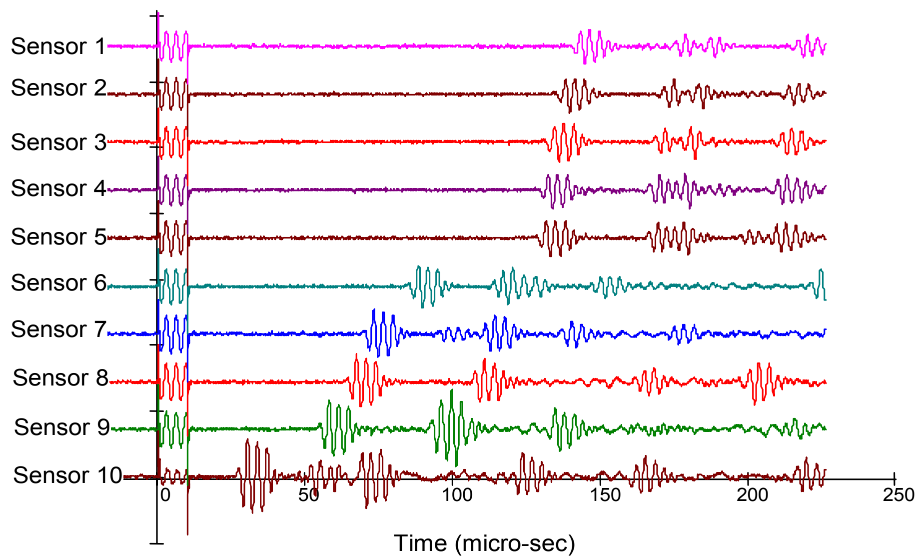

Figure 1 Reception signals on PWAS #1 to 10 when a constant-amplitude tone busrt applied to PWAS #11

Presently, one difficulty in detecting and localizing damage comes from the presence of noise hiding the original signals. In practice, signals collected on actual systems contain various disturbances from the environment. The computation procedure also can introduce noise. Noise has high frequency, which will affect the detection of high frequency components related to damage. Therefore, it is necessary to include a denoising process before signal analysis. In our research, the denoising is implemented by filtering and also by discrete wavelet transform, to ensure the reliability and accuracy of damage detection.

2. Data analysis

To find an efficient signal processing method for the nondestructive evaluation, structural health monitoring and damage detection, we have investigated several methods. Examples using simulated and experimental signals are provided. The experimental signals were obtained by piezoelectric wafer active sensors (PWAS) operating in transmitter and receiver modes. Short time Fourier transform (STFT), wavelet analysis, and filtering were used for the signal processing and analysis. All programs were developed in MATLAB.

The STFT method can analyze a non-stationary signal in the time domain through a segmented algorithm. Through a moving window process, the original signal is broken up into a set of segments, and each segment is processed by the conventional Fast Fourier transform (FFT) algorithm. In the end, all the results in frequency domain are summed up. The effects of two parameters, the window length and the time interval between two consecutive windows, were investigated. For the time-frequency plotting, color code was used to represent the amplitude of each point in the time-frequency space. We developed an STFT graphical user interface (GUI) to control the analyzing procedure since there is no function available in MATLAB. This program was developed based on the mathematical algorithm of STFT.

The wavelet analysis was implemented using MATLAB functions. It consisted of two parts, the continuous wavelet transform and the discrete wavelet transform. A GUI was developed to allow the selection of several mother wavelets, levels, and length scales. The continuous wavelet transform (CWT) was used to produce a spectrum of time-scale vs. amplitude. Another spectrum of time-frequency vs. amplitude was also generated according to the quasi-relationship between the scale and the frequency. Considering that a particular frequency may need special attention, the coefficients at a certain frequency (scale) was generated as well. The discrete wavelet transform (DWT) was used for denoising. A DWT algorithm to automatically generate the best DWT level was developed. Moreover, the DWT denoising capability is compared with other denoising methods, such as statistical denoising and conventional filtering.

2.1 DWT denoising

Figure 2 shows the DWT denoising resulting plots. The first signal is the noisy signal. The second signal is the denoised signal: it has weaker amplitude but it preserves the same shape as the original signal. The bottom signal represents the extracted noises. Note that it is one order of magnitude less than the original and denoised signals.

2.2 DWT denoising vs. statistical denoising

For comparison, the statistical denoising results of Demirli and Saniie (2001) were used. We simulated an ideal wave-packet signal with a 100 MHz sampling frequency over a 2μs duration. Gaussian White Noise (GWN) was added to the ideal signal at different signal to noise ratio (SNR). DWT was applied to denoise the signal. At high SNR, the DWT worked well and eliminated most of the noises. As SNR decreased, the quality of DWT denoising also decreased. Unlike the statistical denoising reported by Demirli and Saniie (2001), DWT cannot completely eliminate the noise in the low signal areas. However, DWT denoising is much faster than the statistical denoising.

DWT denoising efficiency is found to be affected by two factors: SNR and sampling frequency. The higher the SNR and/or the sampling frequency are, the more efficient DWT denoising is. A 2μs signal sampled at 100 MHz results in only

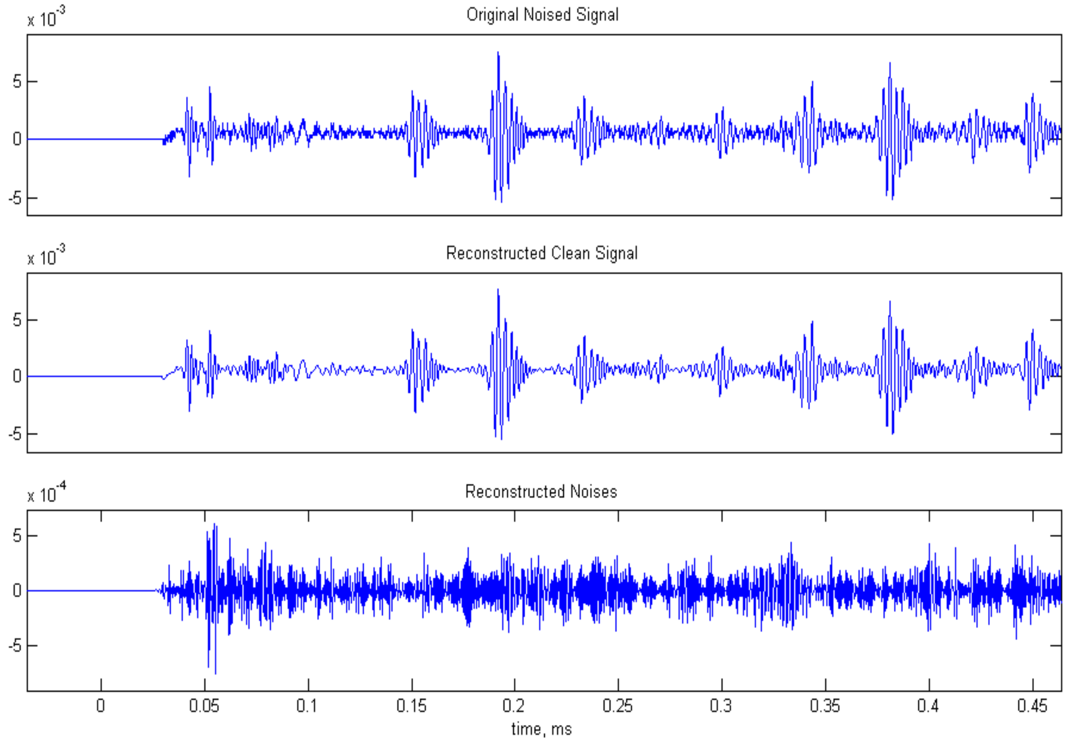

Figure 2 DWT denoising of an experimental signal captured with a PWAS in the pulse-echo mode

200 data points being recorded. To overcome this, we increased the original sampling frequency by inserting extra points of zero amplitude. The number of points inserted between each point of original points was m. Thus, the total number of points was increased from N to $N^* = N + m \cdot (N-1)$. We call m the *densification factor*.

Figure 3 shows the comparisons of signal denoising with DWT at different levels and with different densification factors. Figure 3a shows the original signal with noise level SNR=5. Figure 3b shows the DWT denoised signal superposed on the ideal signal. In obtaining this results, we applied a densification factor m = 8. Figure 3c also shows the DWT denoised signal superposed on the ideal signal. However, this time we used a higher densification factor, m = 50. Note that, for the plot in Figure 3c, the difference between ideal signal and denoised signal is imperceptible. Figure 3d plots the error index (logarithm scale) for densification of m = 8 and m = 50, respectively. It is noticed that using a higher densification factor gives a smaller error. It is also noticed that increasing the DWT level reduces the error in a log-lin manner. However, after a certain DWT level, the denoising process breaks down, and a drastic increase in error is experienced. Thus, a critical DWT level exists at which the denoising is optimal. The value of this critical DWT level depends on the densification factor, m.

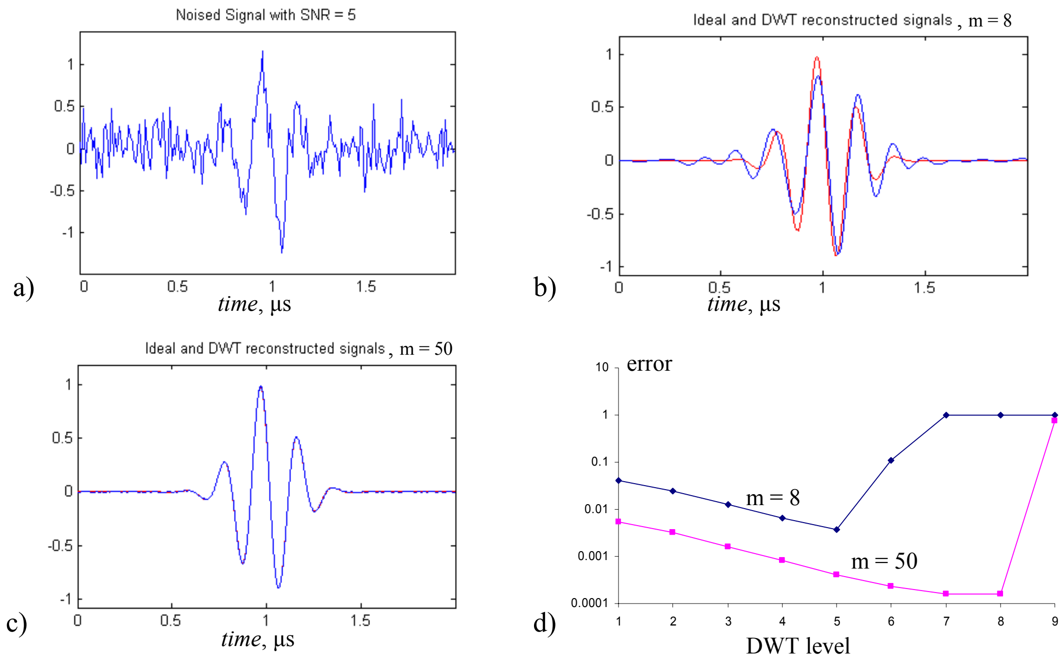

Figure 3 Comparison of signal denoising: a) original noised signal with SNR = 5; b) low quality denoising with m = 8, level =1; c) high quality denoising with m = 50, level = 5; d) variations of error index at different level of m = 8 and m = 50.

2.3 *Wavelet* denoising vs. *filtering* denoising

We compared denoising by DWT with denoising by filtering. The GUI program allowed users to choose filtering parameters, the filter types, filtering methods, and filtering functions. Figure 4 shows results obtained with Chebyshev type II filter of order 3 using bandpass filtering with rolloff frequencies of 3 MHz and 10 MHz. It is seen that filtering does not work as well as DWT on signal denoising, though it is a relatively easier to implement. Another disadvantage of using conventional filtering is the need to assign threshold frequencies (one for lowpass and highpass filters, two for bandpass and bandstop filters).

2.4 Spectrum analysis: *CWT vs. STFT*

Time-scale/frequency spectrums were generated with the CWT method. The GUI parameters included the selection of the mother wavelet, the scale range, and/or the specific scale of interest. An example of the CWT analysis performing on a pulse-echo signal is shown in Figure 5. The CWT analysis was applied after DWT denoising. Figure 5 has both the time-scale and time-frequency spectra, b and c respectively. The time-frequency coordinates provide a more conventional way of interpreting the data. It helps us find amplitude peaks and their location in time and frequency. For example, in Figure 5c, the peak at time around 0.2µs is observed at a frequency around 300 kHz. This is the wave packet observed in the time signal, Figure 5a. The small dots in the background are the processing noise. An important feature of CWT is the capability to analyze the variation in time of a particular frequency (level) component of the signal. This is obtained directly by plotting the CWT coefficients corresponding to the frequency of interest. Figure 5d is a plot of CWT coefficients at frequency 300 kHz.

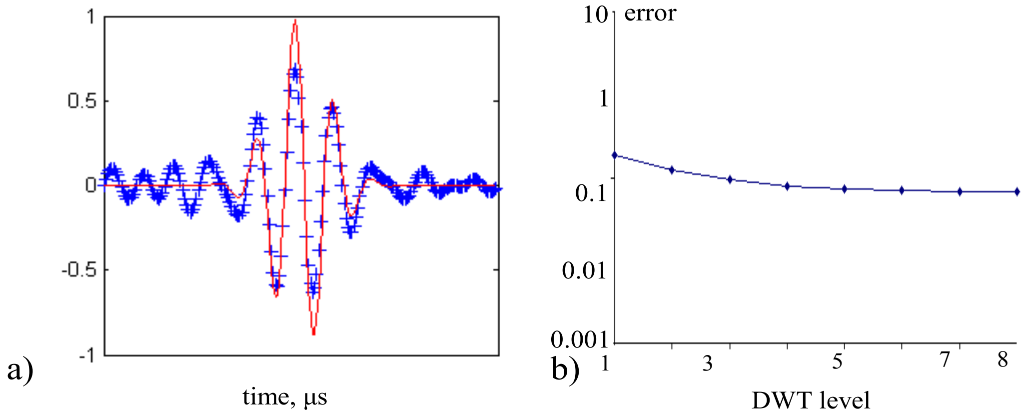

Figure 4 Denoising with filtering: a) ideal signal and filtering denoising signal; b) error index

For the STFT analysis, we constructed a GUI that allowed us to select the window type (rectangular, Hanning, Hamming or Kaiser), window size and the step size. The window size and the step size were defined as a percentage of the original signal length. Figure 6 presents the results of the STFT analysis using a Hanning window. The "single window FFT" of Figure 6 is the result of applying the FFT to the signal selected by the window shown in Figure 5a (in red solid line). Time-frequency amplitude spectrum is presented as contour plot and spectrogram respectively (Figure 6c and d). Compared with the results from CWT, the first thing noticed is that STFT can not provide the frequency analysis for one frequency of concern. Besides, the STFT spectrogram has more background noise, due to the disturbance and loss of precision during the programming.

2.5 Comparison between STFT and WT

The common characteristics of STFT and WT are that both give 2-dimensional spectra for time-frequency analysis. Yet, they are different in several aspects. The basic difference is that wavelet uses a size-adjustable window more advantageous than the fixed window used by STFT (recall that STFT processes the signal with a sliding window having constant length in time). When the local area has a high frequency, the window will be shorter, while when the local area has a low frequency, the window will be longer. Though we provided a single-window FFT plot in the STFT GUI to help the users select the optimal window length, it was still hard and inconvenient to get the best results. From spectra in Figure 6c and 6d, we can see that there is severe background noise in the high frequency area, caused by the processing of STFT. In CWT, the window length is adjusted automatically by the CWT algorithm according to the local frequency scale.

Another advantage of CWT over STFT is that it can extract the coefficients at a certain frequency of interest. This is useful for monitoring some critical frequency components to the performance of the structure. Other advantages of the wavelet analysis are related to denoising. STFT can not do the denoising, and other approaches, like statistical processing or filtering, need to be used. On the other hand, the most practical and convenient DWT denoising is very quick and convenient, considering its integration ability. In our vision, we intend to integrate the pre-processing module, the denoising module, the STFT and CWT modules into an automatic signal analyzer for structural health monitoring and NDE. This analyzer has the potential of being fast and efficient, precise and reliable. The modular construction will allow us to add new modules easily if needed.

3. Conclusion

Several methods are used for signal processing in structural health monitoring on signals collected by PWAS sensor. The results are presented and compared. It is found that STFT is easy to understand and use, while wavelet analysis has a wide application and can be used for both denoising and spectrum analysis. It is hard to say which one is advantageous over the other one. Our future work in this research is aimed to integrated all the functional modules to build an automatic signal analyzer to fit various SHM situations.

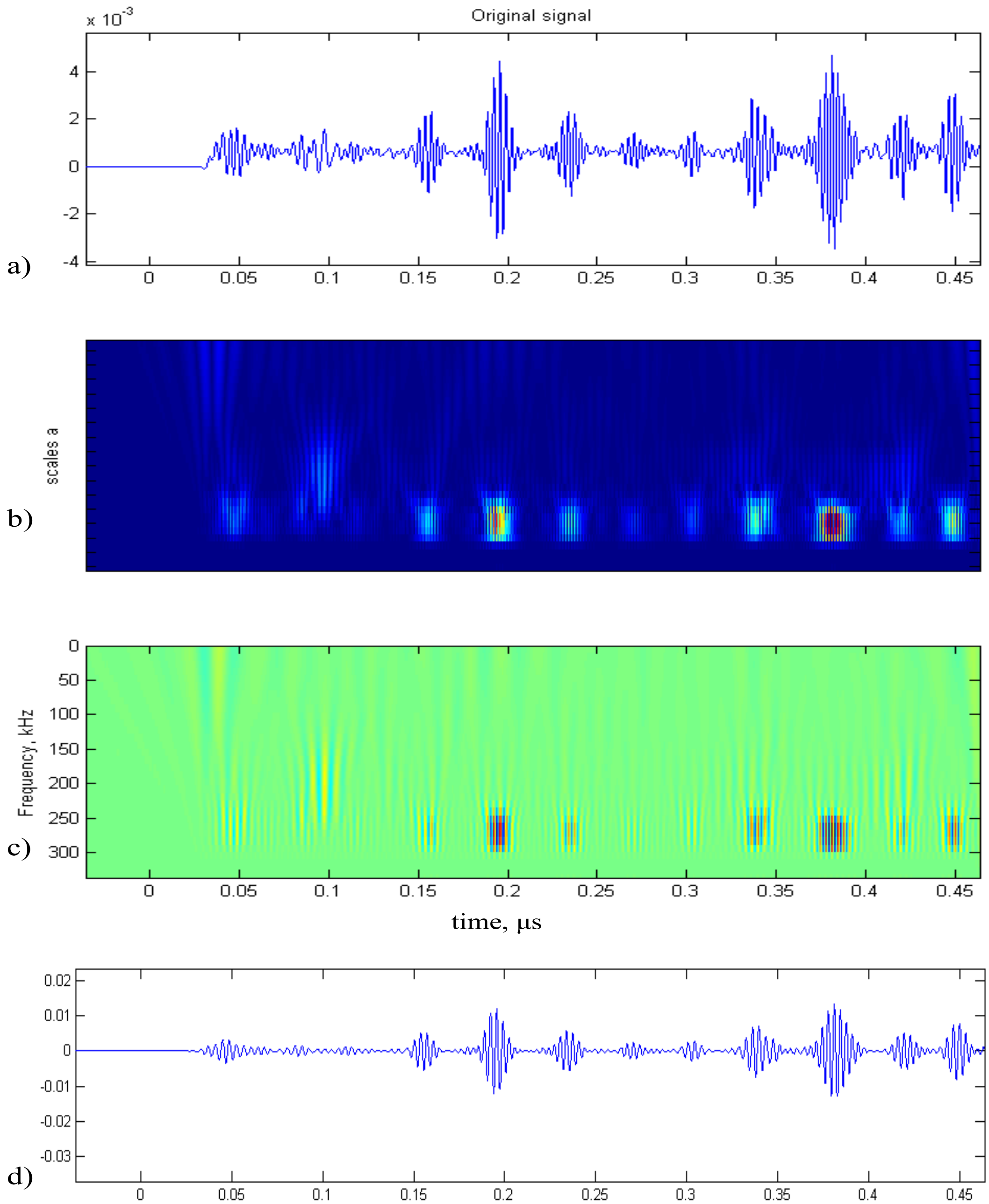

Figure 5 CWT spectrum in time-scale and time-frequency spaces. d) CWT coefficients at frequency 300 kHz.

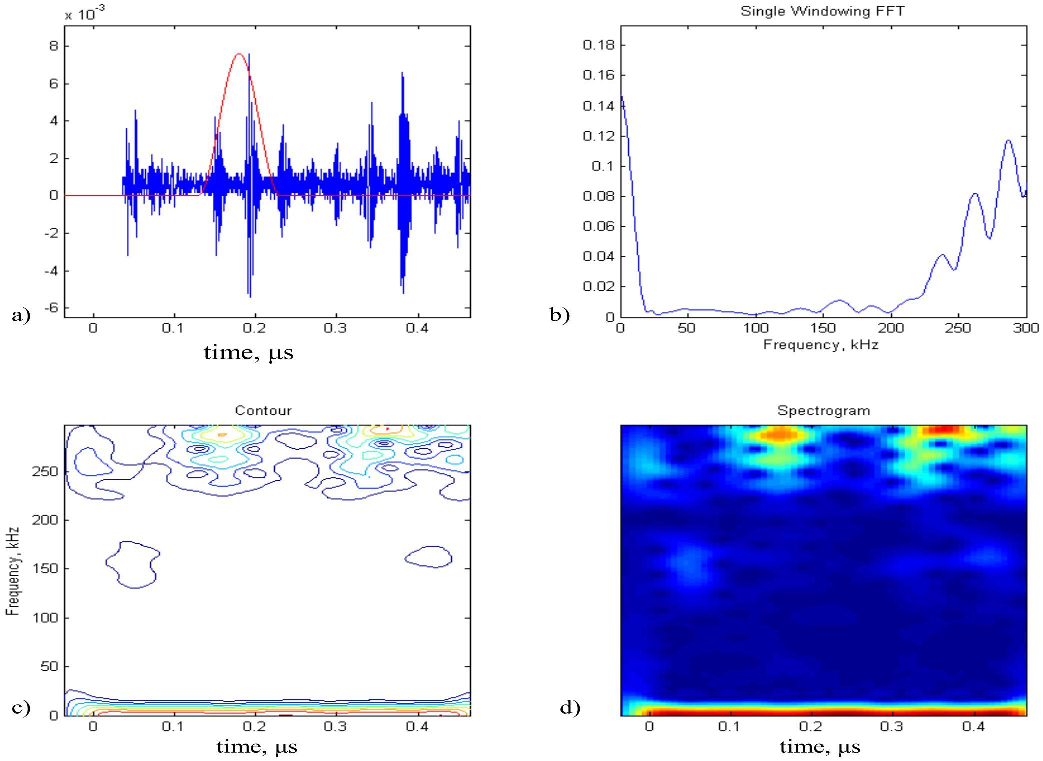

Figure 6 Plots of STFT a) original noised signal, with the single window in red line for local analysis; b) FFT spectrum of windowed signal; c) time-frequency representation via STFT contour; d) time-frequency representation via STFT spectrogram.

4. References

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