Journal of Zhejiang University SCIENCE
ISSN 1009-3095
http://www.zju.edu.cn/jzus
E-mail: jzus@zju.edu.cn

Identification of diesel front sound source based on continuous wavelet transform*

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Received May 16, 2003; revision accepted Sept. 21, 2003

Abstract: Acoustic signals from diesel engines contain useful information but also include considerable noise components. To extract information for condition monitoring purposes, continuous wavelet transform (CWT) is used for the characterization of engine acoustics. This paper first reviews CWT characteristics represented by short duration transient signals. Wavelet selection and CWT are then implemented and wavelet transform is used to analyze the major sources of the engine front's exterior radiation sound. The research provides a reliable basis for engineering practice to reduce vehicle sound level. Comparison of the identification results of the measured acoustic signals with the identification results of the measured surface vibration showed good agreement.

Key words: Acoustic signals, Wavelet transform, Diesel engine, Sound source identification
doi:10.1631/jzus.2004.1069 **Document code:** A **CLC number:** TB53

INTRODUCTION

Study of engine noise had been carried out since the early stages of engine development. In 1931, Ricardo first found a descriptive relationship between the combustion pressure rise and the noise produced (Priede, 1980). Later, a number of parameters in determining engine noise development, which included the first and second derivatives of cylinder pressure, were investigated. These methods were effective in revealing the relationship between engine combustion and noise. Some of them still play an important role in identifying the sources of engine noise (Schaberg *et al*., 1990).

The identification of engine sound source has been a focus of engine researches, some of which were very successful. Vibration based techniques have been the mainstay of diesel engine measurements since their inception. In contrast, acoustic measurement of engines has received only scant attention due to the fact that acoustic signals from engines include considerable noise components. It seems quite reasonable to assume that to extract useful information from contaminated acoustic signals of an engine would pose practically insurmountable problems.

The obvious problems do not mean that the identification of diesels sound source by acoustic signals is not feasible. Acoustic measurement can be performed at a distance from the engine, avoiding safety risks and obviating the need for high-temperature vibration testing equipment with its associated mounting considerations. In addition, acoustic signals can actually be more sensitive to certain physical processes than surface vibration.

* Project (No. 50175078) supported by the National Natural Science Foundation of China

The last few years have witnessed significant progress in the capabilities of acoustic instrumentation, and signal processing techniques used in speech and image recognition.

Conventional techniques, such as power spectrum analysis, time-domain averaging, adaptive noise cancellation, demodulation analysis, time-series analysis, are well established. However, there are difficulties in identification of diesel sound sources using acoustical signals, because conventional techniques are based on the assumption of stationarity of the signals. A number of new techniques have been proposed to deal with non-stationary signals. Among these new techniques, wavelet analysis has particular advantages for characterizing signals at different localization levels in time and frequency domains. It has wide applications in many engineering fields such as signal processing, image processing, pattern recognition, seismology, machine visualization, etc.

However, the applications of the wavelet transform to the identification of diesels sound source by acoustic signals has been rarely investigated. This paper focuses mainly on study of acoustic signals generated from a test engine to identify their sound sources. The theoretical modeling of CWT is described in Section 2. In Section 3, the test rig and results of traditional spectrum analysis and of CWT are presented and discussed. Finally, the conclusions are drawn in Section 4.

THEORETICAL MODELING

Continuous wavelet transform

Wavelet analysis is becoming a common tool for analyzing localized power variations and vibration signals within a time series (Morlet *et al.*, 1982; Grossmann and Morlet, 1984). By decomposing a time series into time-frequency space, the dominant modes of variability and how those modes vary in time can be determined. It is assumed that there is a time series, x_n, that has equal time spacing δ_t with n=0, 1, 2,⋯, N−1. There is a wavelet function, $\Psi_0(\eta)$, that depends on a non-dimensional "time" parameter η. To be "admissible" as a wavelet, this function must have a mean value of zero and be localized in both time and frequency space (Torrence and Compo, 1998). The continuous wavelet transform of a discrete sequence x_n is defined as the convolution of x_n with a scaled and translated version of $\Psi_0(\eta)$:

$$W_n(s)=\sum_{k=0}^{N-1}x_k\psi^*[\frac{(k-n)\delta_t}{s}] \qquad (1)$$

where * indicates the complex conjugate. By varying the wavelet scale and translating along the localized time index n, a picture showing the amplitude of vibration signal versus the scale and time can be constructed. In order to estimate the continuous wavelet transform, the convolution should be done N times for each scale, where N is the number of points in the time series. By choosing a number of N points, the convolution theorem allows us to construct all N convolutions simultaneously in a Fourier space using a discrete Fourier transform (DFT). The DFT of x_n is:

$$\hat{x}_k=\frac{1}{N}\sum_{n=0}^{N-1}x_n\mathrm{e}^{-2\pi ikn/N} \qquad (2)$$

where k=0, 1, 2,⋯, N−1 is the frequency index. In the continuous limit, the Fourier transform of a function $\psi(t/s)$ is given by $\hat{\psi}(s\omega)$. By the convolution theorem, the wavelet transform is the inverse Fourier transform of the product:

$$W_n(s)=\sum_{k=0}^{N-1}\hat{x}_k\ \hat{\psi}^*(s\omega_k)\mathrm{e}^{i\omega_k n\delta_t} \qquad (3)$$

where

$$\hat{\psi}(s\omega_k)=(\frac{2\pi s}{\delta_t})^{1/2}\ \hat{\psi}_0(s\omega_k)$$

and

$$\sum_{k=0}^{N-1}|\hat{\psi}(s\omega_k)|^2=N$$

Choice of wavelet function and scale factor

In this paper, mother wavelet is used to analyze data. Mother wavelet is Morlet wavelet which consists of a plane wave modulated by a Gaussian function:

$$\psi_0(t) = \pi^{-1/4} e^{i\omega_0 t} e^{-t^2/2},$$
$$\hat{\psi}_0(s\omega) = \pi^{-1/4} e^{-(s\omega-\omega_0)^2/2},\ \omega > 0, \quad (4)$$

where ω_0 is the non-dimensional frequency set to 6.

Once a wavelet function is chosen, it is necessary to choose a set of scales s to be used in the wavelet transform. An orthogonal wavelet is limited to a discrete set of scales as given by Torrence and Compo (1998). However, non-orthogonal wavelet analysis and an arbitrary set of scales can be used to build up a more complete picture. It is convenient to write the scales s of non-orthogonal as fractional powers of the following two equations:

$$s_j = s_0 2^{j\delta_j},\ j=0, 1, 2, \ldots, J \quad (5)$$

$$J = \delta_j \log_2(N\delta_t / s_0) \quad (6)$$

where s_0 is the smallest resolvable scale and J is the largest scale. The s_0 should be chosen so that the equivalent Fourier period is approximately $2\delta_t$. The choice of a sufficiently small δ_j depends on the width in spectral-space of the wavelet function. For Morlet wavelet, a δ_j of about 0.5 is the largest value that still gives adequate sampling in scale.

Because Morlet wavelet is in general complex, the wavelet transform $W_n(s)$ is also complex. Therefore, the transform can then be divided into the real part, $\mathrm{Re}\{X_n(s)\}$, and imaginary part, $\mathrm{Im}\{X_n(s)\}$. It can also be expressed in amplitude, $|W_n(s)|$, and phase, $\tan^{-1}[\mathrm{Im}\{X_n(s)\}/\mathrm{Re}\{X_n(s)\}]$. Finally, the wavelet power spectrum can be defined as $|W_n(s)|^2$. Following the method of Meyers and Kelly (1996), the relationship between the equivalent Fourier period and the wavelet scale can be derived. Morlet wavelet with ω_0=6 has a λ value of $1.03s$, where λ is the Fourier period. It indicates that for Morlet wavelet, the wavelet scale s is almost equal to the Fourier period.

Time-averaged wavelet spectrum

If a vertical slice through a wavelet plot is a measure of the local spectrum, then the time-averaged wavelet spectrum over a certain period is:

$$\bar{W}_n^2(s) = \frac{1}{N_a}\sum_{i=n_1}^{n_2} |W_i(s)|^2 \quad (7)$$

where the index n is arbitrarily assigned to the points between n_1 and n_2. N_a=(n_2−n_1+1) is the number of points. By repeating Eq.(7) at each time step, a wavelet plot is created.

When the number of points covers all the local wavelet spectra in Eq.(7), the global wavelet spectrum is given:

$$\bar{W}_n^2(s) = \frac{1}{N}\sum_{j=n_1}^{n_2} |W_j(s)|^2 \quad (8)$$

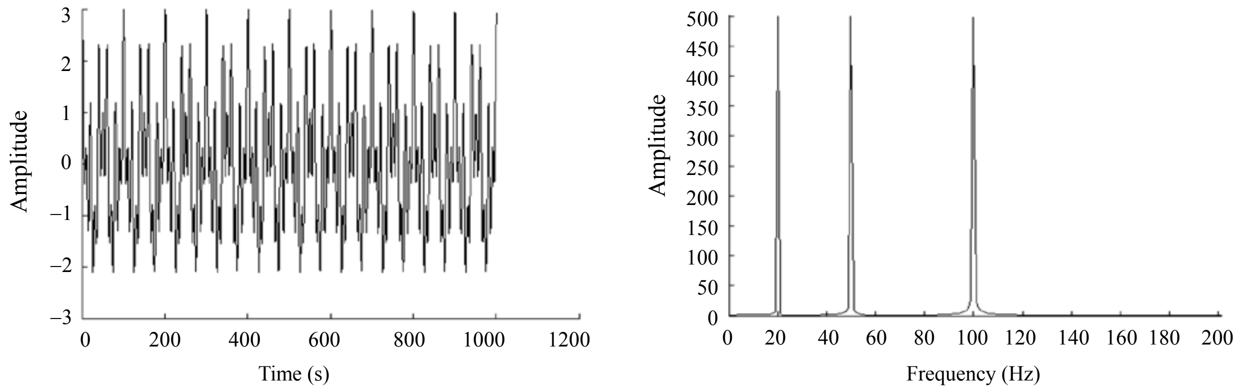
where N is the number of sampling points, j=0, 1, …, J. It reflects the distribution of energy of wavelet power spectrum in the direction of scale.

Test analysis

As an example, a signal represented as X_1 ($X_1(t)$=cos(2π20t)+cos(2π50t)+cos(2π100t)) is a stationary signal, because it has frequencies of 20, 50 and 100 Hz at any given point of time. This signal and its FFT are plotted in Fig.1 and its continuous wavelet transform (CWT) is plotted in Fig.3. In another example, a signal X_2 with three different frequency components in three time intervals is plotted in Fig.2 and its CWT is plotted in Fig.4. This is a non-stationary signal. The time interval 0 to 300 ms includes a 20 Hz sinusoid, the interval 300 to 600 ms corresponds to a 50 Hz sinusoid, and the interval 600 to 1000 ms has a 100 Hz sinusoid.

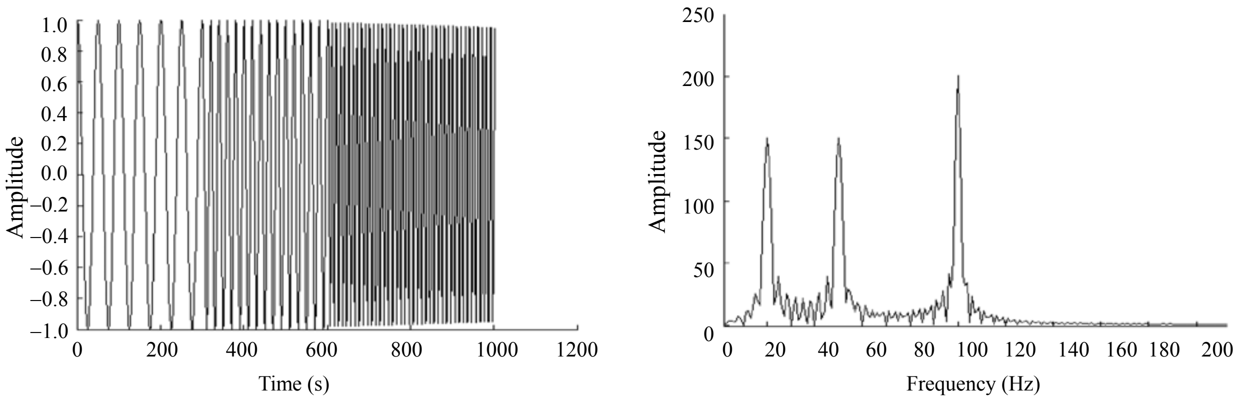
Comparing the Figs.1 and 2, it is apparent that there is similarity between the two spectra. Both of them show three spectral components at exactly the same frequencies, i.e., at 20, 50 and 100 Hz. Both of the signals involve the same frequency components, but the first one has these frequencies at all times, the second one has these frequencies in different time intervals. The FFT gives the spectral content of the signal, but it does not provide information regarding the time when those spectral components appear. Therefore, FFT is not a suitable technique for non-stationary signal.

In Figs.3 and 4, the 2-D plots show the dimensionless time and frequency level on the plane, the energy axis indicates the vibration amplitude. Comparison of Fig.3 and Fig.4 reveals that the two signals can easily be distinguished. Therefore, the continuous wavelet transform is more suitable than FFT for non-stationary signal.



(a) (b)

Fig.1 Waveforms (a) and spectrum (b) of signal X_1



(a) (b)

Fig.2 Waveforms (a) and spectrum (b) of signal X_2

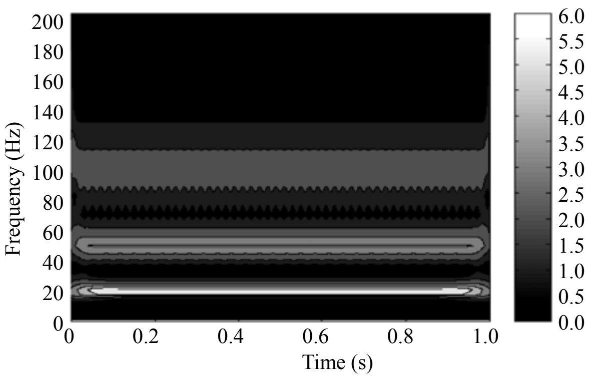


Fig.3 CWT of signal X_1

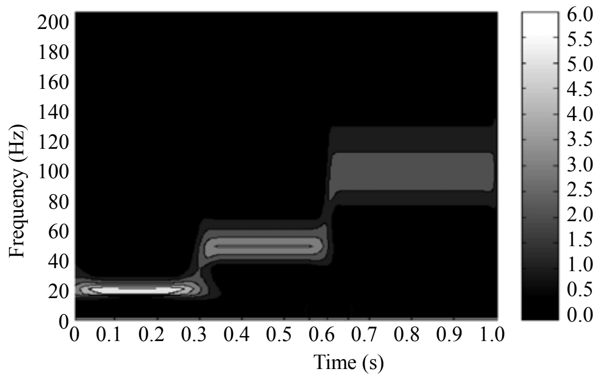


Fig.4 CWT of signal X_2

ENGINE NOISE SOURCE IDENTIFICATION

Experiment procedure

Measurement consisted of a microphone in conjunction with the charge amplifier, the FFT analyzer and PC for additional computation. The sampling frequency was 40 kHz.

The acoustic signals were obtained from a four-stroke diesel engine in a semi-anechoic laboratory with acoustic wedges on all surfaces except on the floor. The engine was installed in the center of the room. A microphone was positioned 1 m away from the engine front. Since there was no sound reflection to the engine sound radiation surfaces in the laboratory, the sound signals from other side of the engine were correspondingly small at the measurement position of the engine front. Therefore, the measured signals should mainly mirror the front sound energy. This was confirmed in sound intensity experiments (Hao and Han, 2003). The sound signals were fed into a computer through the microphone. The results were then post-processed using the CWT, and presented in two-dimensional contour plots to show the more accurate time-frequency locations of the events. The real part of the wavelet coefficients was displayed, the abscissa being time and the ordinate being frequency. Light gray and white regions of the graph present the positive wavelet coefficients, dark gray and black regions the negative values. During the measurements, the revolution speed of the diesel engine was 3600 rpm and the load was from 0 to 179 Nm.

Results and discussion

The recorded acoustic wave signals from the diesel engine are shown in Fig.5a. The continuous wavelet transform of the acoustic signal is presented in Fig.5b. The contour plot of the CWT presents the sound energy distribution of the engine front in time-frequency domain. The time-frequency distribution describes simultaneously when a signal component occurs and how its frequency spectrum develops with time. As the positions of ridges represent the distribution of major sound energy, it is evident from the map of Fig.5b that the major sound energy frequency is around 100 Hz and 200 Hz, respectively. On the other hand, there is evident energy distribution periodicity corresponding to the engine's work cycle in Fig.5b. Since the rotation speed of the engine is 3600 rpm when the acoustic measurement was conducted, and the ignition period is about 0.033 s, some acoustic responses of engine front to engine combustion can also be found from 200 to 600 Hz in Fig.5b. It confirms the findings in previous theoretical and experimental studies (Grossmann and Morlet, 1984) that engine acoustic signals are periodical and unsteady.

Fig.6a shows the vibration signals of the oil sump in the time-frequency plane. The wavelet transform of signals is shown in Fig.6b. The map shows that most of the energy is around 100 Hz and that some scattered spots appear around 500 Hz.

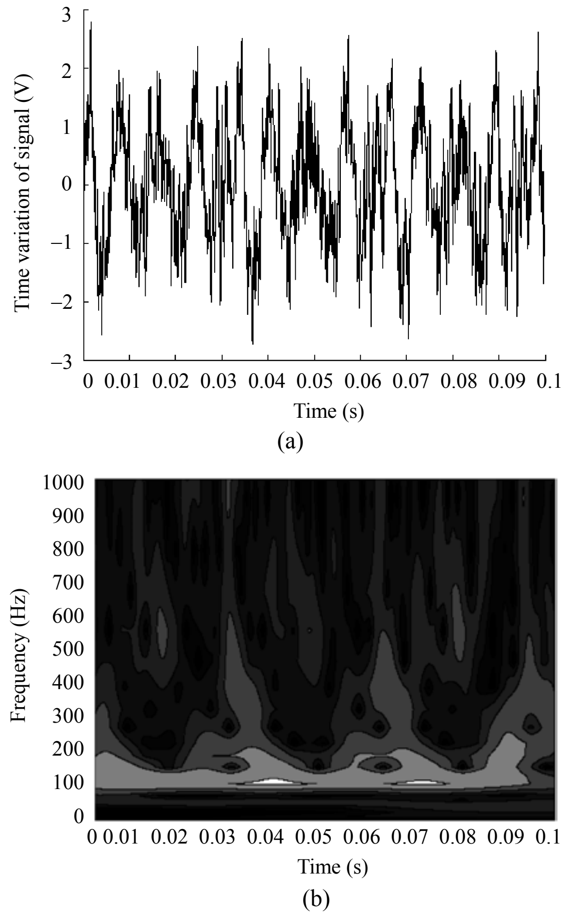


Fig.5 Spectrum analysis of acoustic signals
(a) Sound pressure signals in diesel front; (b) CWT of signals

Fig.7 shows the vibration of the front timing gear cover in the time-frequency plane. The energy is concentrated around 200 Hz. It can be found from the Figs.6 and 7 that the sound energy periodicity is related to the work cycle and rotation speed of the engine.

After the measurements were conducted, the first analysis task was to determine the sources of various components. This is because, as an efficient sound control strategy for an engine, the strongest sound sources must be identified first. The results showed that the front sound signals of the diesel were periodical and unsteady. The major frequency components of the sound signals were around 100 Hz and 200 Hz, that are similar to the major frequency components of the vibrations in the oil sump and timing gear cover, respectively. Therefore, the vibrations of the oil sump and front timing gear cover were proved to be the main sound sources in the front of the tested diesel engine.

CONCLUSION

Wavelet transform was applied to the acoustic signal analysis in order to identify the sound sources of a diesel engine. The wavelet transform permits the characterization of a one-dimensional acoustic signal as a two-dimensional representation distributed in time and frequency. As a practical application to diesel front sound sources, the results of three tests were analyzed. The main objective was to identify the sound sources of a diesel engine. From the analysis, the following conclusions were

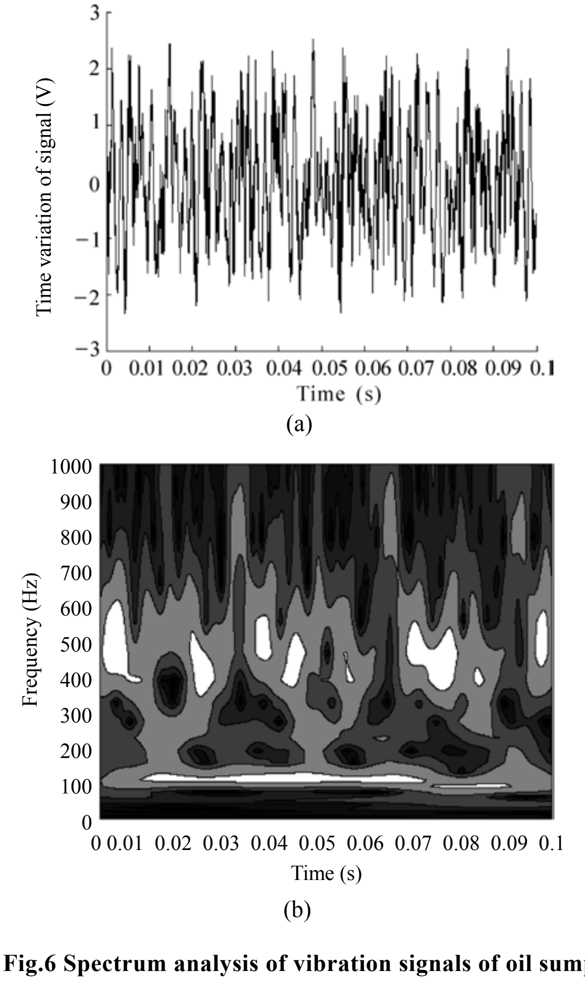


Fig.6 Spectrum analysis of vibration signals of oil sump
(a) Vibration signals of oil sump of diesel; (b) CWT of the signals

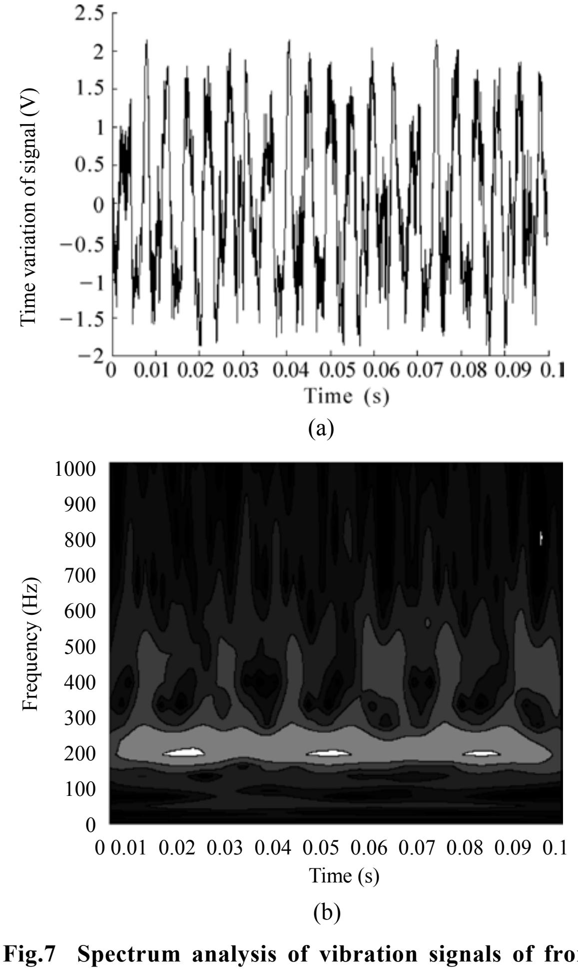


Fig.7 Spectrum analysis of vibration signals of front timing gear cover
(a) Vibration signals of the front timing gear cover; (b) CWT of the signals

obtained.

Continuous wavelet transform of acoustic signal enables the determination of a signal frequency at any time. In the wavelet coefficient map, the signals of very different frequencies are displayed. A time-frequency map, constructed by plotting the wavelet coefficients against the time (translation) and scale parameter (period or frequency), shows an alteration of acoustic waves.

In the contour maps measured from the front sound of a diesel engine, it was evident that the oil sump and timing gear cover are the main sound sources of the engine front. The vibration of the oil sump is responsible for the sound around 100 Hz, and the vibration of the front timing gear cover is responsible for the sound around 200 Hz.

References

Grossmann, A., Morlet, J., 1984. Decomposition of hardy functions into square integrable wavelets of constant shape. *Journal on Mathematical Analysis, Society for Industrial and Applied Mathematics*, **4**:723-736.

Hao, Z., Han, J., 2003. Investigation on noise sources identification of diesel engine by means of acoustic signals Analysis. *Chinese Internal Combustion Engine Engineering*, **24**(5):25-29.

Meyers, S.D., Kelly, B.G., 1996. An introduction to wavelet analysis in oceanography and meterorology: with application to the dispersion of Yanai waves. *Mon. Wea. Rev.*, **121**:2858-2866.

Morlet, J., Arens, G., Furgeau, I., Giard, D., 1982. Wave propagation and sampling theory. *Geophysics*, **2**.

Priede , T., 1980. In Search of Origins of Engine Noise−An Historical Review. SAE 800534, p.2039-2069.

Schaberg, P.W., Pride, T., Dutkiewicz, R.K., 1990. Effects of Rapid Pressure Rise on Engine Vibration and Noise. SAE 900013, p.1-13.

Torrence, C., Compo, G.P.A., 1998. Practical guide to wavelet analysis. *Bull. Amer. Metero. Soc.*, **79**(1):61-78.