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Feature extraction of machine sound using wavelet and its application in fault diagnosis

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Abstract

Machine sound always carries information about the working of the machine. But in many cases, the sound has a very low SNR. To obtain correct information, the background noise has to be removed or the sound must be purified. A de-noising method is given in this paper and is successfully used in feature sound extraction. We can easily diagnose a machine using the purified sound. This de-noising method is based on the wavelet technique and uses the Morlet wavelet as the mother wavelet, because its time–frequency resolution can be adjusted to adapt to the signal to be analyzed. The method is used for extracting the sound of some vehicle engines with different types of failure. The feature sound is extracted successfully. © 2001 Published by Elsevier Science Ltd.

Keywords: Fault diagnosis; Wavelet; Feature extraction

1. Introduction

Machine sound usually reflects the working condition of the machine. Many experienced operators can diagnose a machine just by listening to its sound. But very often, the feature sound of the machine is immersed in heavy noise and the operators can hardly make out any changes in the sound. Also, we cannot find any symptoms in the waveform and the Fourier spectrum of the sound at this time. Thus, to obtain the useful information that is hidden in the noisy signal an effective method for feature extraction has to be used.

Wavelet analysis is an effective tool for nonstational signal processing and has been used in many research fields. It has also been used for feature extraction and noise elimination, such as *matching pursuits* produced by Mallat and his collaborators [1,2] and *soft-thresholding de-noising* developed by Donoho [3]. While in many mechanical dynamic signals, such as the acoustic signals of an engine, Donoho's method seems rather ineffective, the reason for their inefficiency is that the feature of the mechanical signals is not considered. Therefore, the idea of Donoho's method and the feature of the sound are combined, and a de-noising method based on the Morlet wavelet is produced. When applied to an engine sound extraction, this method can be seen to be very effective.

This paper is organized as follows. In Section 2, the proposed de-noising method is used for a simulated signal, which shows the powerful capacity of the method for feature extraction. In Section 3, the experimental setup is introduced. In Section 4, some signals sampled from a ball bearing and the reciprocating compressor are processed for feature extraction using the de-noising method. In Section 5, the conclusions are given.

2. Wavelet and its application for feature extraction

2.1. Review of wavelet transform

The wavelet was originally introduced by Groupillaud et al. in 1984 [4]. Let $\psi(t)$ be the basic wavelet function or the mother wavelet, then the corresponding family of daughter wavelets consists of

$$\psi_{a,b}(t) = |a|^{-1/2}\psi\left(\frac{t-b}{a}\right), \tag{1}$$

where a is the scale factor and b the time location, and the factor $|a|^{-1/2}$ is used to ensure energy preservation.

The wavelet transform of signal $x(t)$ is defined as the inner product in the Hilbert space of the L^2 norm, as shown in the following equation:

$$W(a,b) = \langle \psi_{a,b}(t), x(t) \rangle = |a|^{-1/2} \int x(t)\psi^*_{a,b}\, \mathrm{d}t. \tag{2}$$

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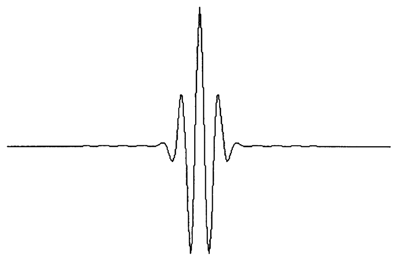

Fig. 1. The shape of the Morlet wavelet.

Here the asterisk stands for complex conjugate. Time parameter b and scale parameter a vary continuously, so the transform defined by formula (2) is also called a continuous wavelet transform, or CWT. The mother wavelet $\psi(t)$ is assumed to lie in $L^2(C)$ and satisfies the admissibility condition:

$$C_\psi = \int_{-\infty}^{\infty} |\hat{\psi}(\omega)|^2/|\omega| \, d\omega < \infty \tag{3}$$

where $L^2(C)$ is the space of square integrable complex functions, and

$$\hat{\psi}(\omega) = \int \psi(t) \exp(-j\omega t) \, dt. \tag{4}$$

The wavelet transform coefficients $W(a,b)$ can be considered as functions of translation b for each fixed scale a, which give the information of $x(t)$ at different levels of resolution. The wavelet coefficients $W(a,b)$ also measure the similarity between the signal $x(t)$ and each daughter wavelet $\psi_{a,b}(t)$. This implies that wavelets can be used for feature discovery if the wavelet used is close enough to the feature components hidden in the signal.

For many mechanical acoustic signals impulse components often correspond to the feature sound. Thus, the basic wavelet used for feature extraction should be similar to an impulse. The Morlet wavelet is such a wavelet. It is defined as

$$\psi(t) = \exp(-\beta^2 t^2/2) \cos(\pi t). \tag{5}$$

Obviously, it is a cosine signal decaying exponentially on both sides. Fig. 1 illustrates the shape of the Morlet wavelet. It does look like an impulse.

2.2. Feature extraction using the Morlet wavelet

As stated above, the Morlet wavelet can be used as the basic wavelet for feature extraction. But how do we use it for feature extraction?

The most popular algorithm of wavelet transform is the Mallat Algorithm. Though this algorithm can save a lot of computations, it demands that the basic wavelet is orthogonal. The Morlet wavelet is not orthogonal. Thus, the wavelet transform of the Morlet wavelet has to be computed by the original definition, as shown in Eq. (2). Although the CWT brings about redundancy in the representation of the signal (a one-dimensional signal is mapped to a two-dimensional signal), it provides the possibility of reconstructing a signal. A classical inversion formula is

$$x(t) = C_\psi^{-1} \int\int W(a,b)\psi_{a,b}(t) \frac{da}{a^2} \, db. \tag{6}$$

Another simple inverse way is to use Morlet's formula, which only requires a single integration. The formula is [5]

$$x(t) = C_{1\psi}^{-1} \int W(a,b) \frac{da}{a^{3/2}} \tag{7}$$

where

$$C_{1\psi} = \int_{-\infty}^{\infty} \hat{\psi}^*(\omega)/|\omega| \, d\omega. \tag{8}$$

It is valid when $x(t)$ is real and either $\psi(t)$ is analytic or $\hat{\psi}(\omega)$ is real. The condition is satisfied by the Morlet wavelet. If the wavelet coefficients $W(a,b)$, corresponding to feature components, could be acquired, we could obtain the feature components just by reconstructing these coefficients. In calculations, the feature coefficients should be reserved and the irrelevant ones set to zero, then the signal can be purified by using formula (7). Thus, the key to obtaining the purified signal is how to obtain these feature coefficients.

As is known, wavelet coefficients measure the similarity of the signal and each daughter wavelet. The more the daughter wavelet is similar to the feature component, the larger is the corresponding wavelet coefficient. So these large wavelet coefficients are mainly caused by the impulse components in the signal if the signal is transformed by the Morlet wavelet. Reconstructing these large coefficients, we can get the impulse components in the signal. Usually a threshold should be set in advance, and the coefficients that are larger than the threshold are assumed to be feature coefficients. The value of the threshold affects the purified results directly, but it is not easy to choose a proper threshold. An important step in solving this problem was achieved by the work of Donoho and Johnstone [3,6]. Let N be the length of the data, the noise is iid normal Gaussian white noise, and σ the gain of the noise. According to their conclusions, with the threshold $t_N = \sigma\sqrt{2 \log N}$, the noise almost certainly can be removed as N goes to infinity. This conclusion is true only for the orthogonal wavelet transform. The reason is that the iid random noises are still iid after orthogonal transformation. More details can be found in Ref. [3]. The Morlet wavelet is nonorthogonal, so the variables are not iid when transformed. Some researchers have published further discussions on threshold selection for the nonorthogonal wavelet transform during the last few years [7,8]. It was proved that the threshold for the nonorthogonal wavelet was larger than that for the orthogonal. For the Morlet wavelet, the scheme for threshold selection is the same as that for the nonorthogonal wavelet. The basic rule for threshold choice is that the higher the correlation between the random variables, the larger the threshold; the

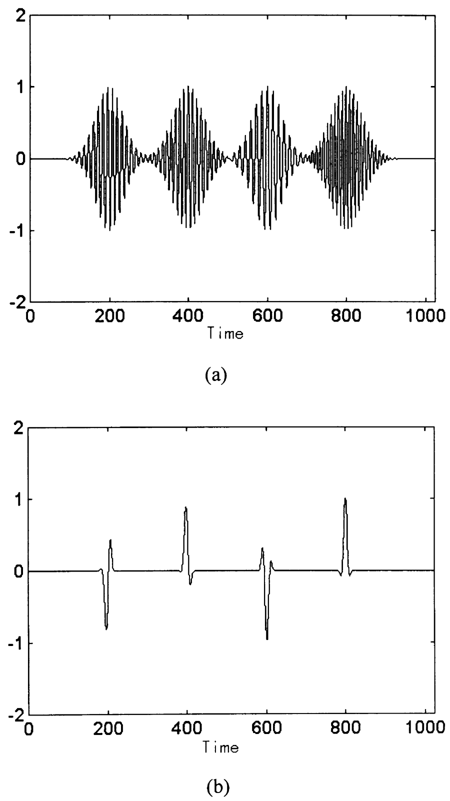

Fig. 2. The two simulated signals.

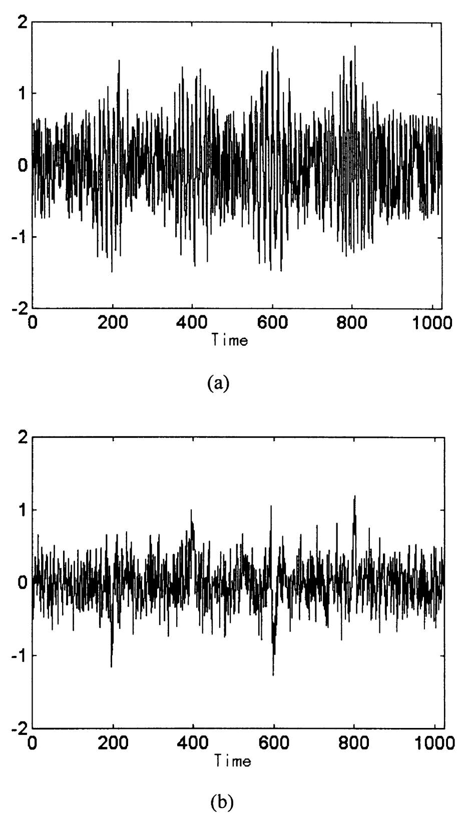

Fig. 3. The two signals with additive white noise.

higher the SNR, the lower the threshold. In practice, the choice of the threshold mainly depends on experience and knowledge about the signal. The quantitative relation between the threshold and the SNR still remains a question.

3. Feature extraction for simulated signals

To verify the capacity for feature extraction of the method introduced above, two examples are given. The two examples are two simulated impulse signals with additive white noise. The noise is standard normal distributed with standard deviation $\sigma = 0.3$. The analysis formulae of the signals are

$$\begin{aligned} y_a(t) = {} & \exp[-(t-200)^2/2400]\cos(\pi t/6) \\ & + \exp[-(t-400)^2/3000]\cos(\pi t/5.4) \\ & + \exp[-(t-600)^2/2700]\cos(\pi t/7) \\ & + \exp[-(t-800)^2/3200]\cos(\pi t/4.7), \end{aligned} \tag{9}$$

$$\begin{aligned} y_b(t) = {} & \exp[-(t-200)^2/80]\cos(\pi t/15) \\ & + \exp[-(t-400)^2/70]\cos(\pi t/18) \\ & + \exp[-(t-600)^2/90]\cos(\pi t/14) \\ & + \exp[-(t-800)^2/60]\cos(\pi t/16). \end{aligned} \tag{10}$$

Let the sampling rate be equal to one. The waveforms of the two signals are illustrated in Fig. 2(a) and (b). Adding white noise, we get the two noisy signals, as shown in Fig. 3(a) and (b). The SNR is 1.6 in Fig. 3(a) and 0.28 in Fig. 3(b).

Using the feature extraction method based on the Morlet wavelet, we can get the two purified signals, as shown in Fig. 4. Obviously, the original signal can be extracted perfectly and this shows that this method is very suitable for impulse extraction. The values of the threshold are one-fifth of the maximum for $y_a(t)$ and one-third of the maximum for $y_b(t)$, respectively. The thresholds are set only by experience, so perhaps the optimal values do exist.

4. Mechanical diagnosis based on feature sound extraction

On many occasions, experienced operators can judge failures of a machine just by its sound. But for a beginner, it is usually very hard to recognize a failure by the sound. And if the noise is too heavy, even those experienced operators cannot recognize the failure or can make a wrong judgement. This indicates that the sound carries information about the condition of the machine and this information is usually immersed in noise. If the feature sound can be extracted from the original sound, the experienced operators will easily recognize the failures. And those operators

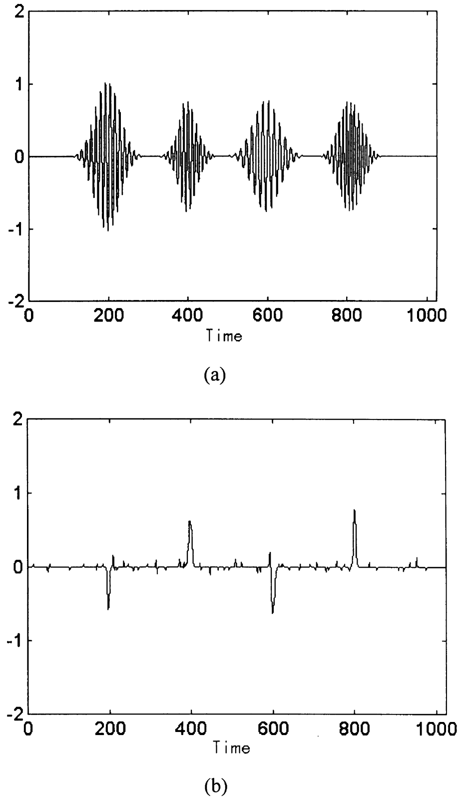

Fig. 4. The two purified signals.

unfamiliar with the feature sound will grasp the character of the feature sound quickly by listening to the purified sound. That is, the purified sound can be a guide to beginners on how to pick the feature sound from the noisy machinery sound. In the following, three automobile engines with different faults are tested. Using the purified sound, we can recognize them correctly.

The acoustic signals are sampled with a microphone. The sampling frequency is 6 kHz with a 2 kHz low pass filter in advance. When we convert these digital files into ".wav" files we can listen to the sound of the engine using a PC. The three engines include a normal engine, an engine with a crankshaft bearing abrasion and an engine with a valve push rod abrasion. For the normal engine, the sound is smooth, rhythmic and in harmony despite the running speed and load. When the bearing is scratched, collision between the crankshaft and the bearing will occur. In this case, the sound is a deep and a rhythmic clunk. The greater the load and the faster the speed, the stronger the sound. When the valve push rod is scratched, the sound is a patter. If the noise is too heavy, the features of these sounds will not be exposed.

Their acoustic signals are illustrated in Fig. 5(a), (b) and (c). From their waveforms, we can see that the energy of high frequency increases when the two faults occur. But there is little difference between Fig. 5(b) and (c). Then compare their FFT spectra, as shown in Fig. 6(a) and (b). There still exists little difference between them. By

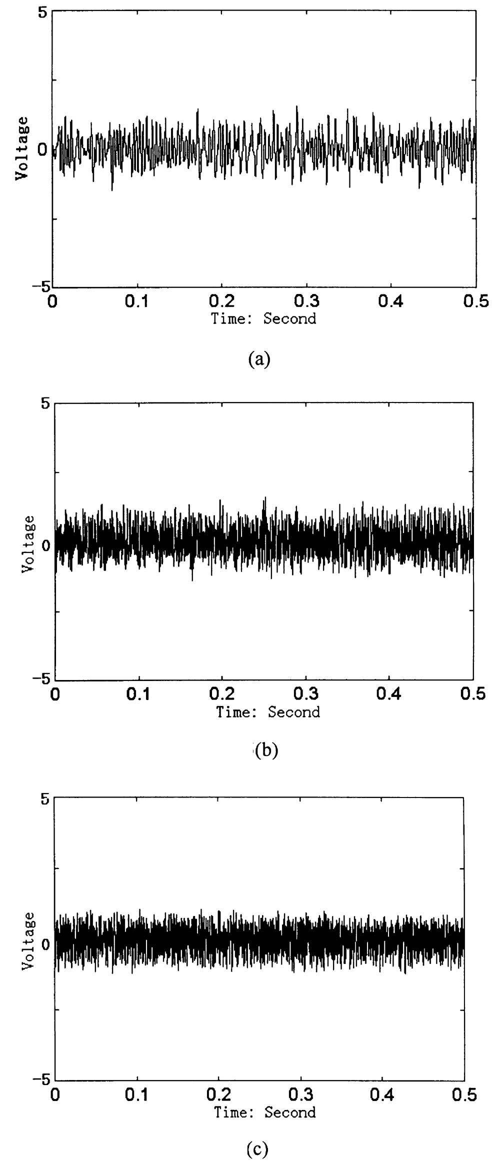

Fig. 5. (a) Acoustic signal of the normal engine. (b) Acoustic signal of the engine with crankshaft bearing abrasion. (c) Acoustic signal of the engine with valve push rod abrasion.

converting these digital files into ".wav" files and listening, we find that the sounds are very noisy and cannot be distinguished.

In fact, a difference does exist between the two signals. We cannot find the difference because of the heavy background noise that blurs the feature structure of the signals. Using the de-noising method based on the wavelet, we can remove the noisy components and distinguish them. The thresholds are taken as one-fourth of the maximum of the signal. The reason for this selection is that the SNR of the signals are low. The purified signals are illustrated in Fig. 7(a) and (b). There exists a sharp difference between the two figures. Thus it can be easily proved that the impulses are exposed after performing de-noising. Listening to the sound of the purified signals, we can find that the sound of the two fault engines becomes

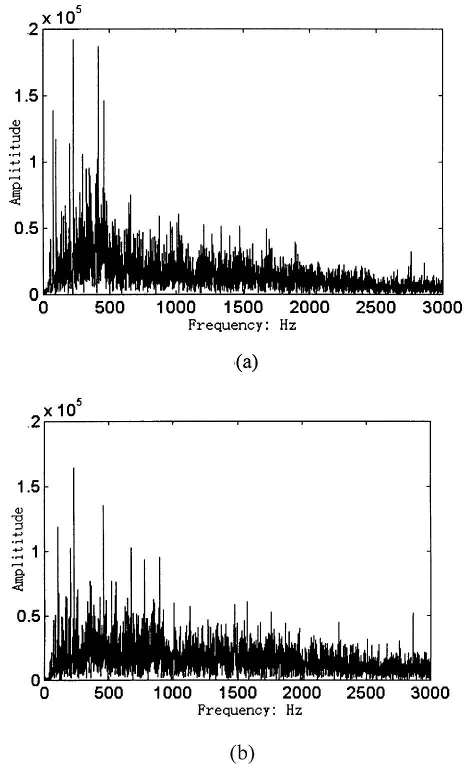

Fig. 6. (a) FFT spectrum of the engine with crankshaft bearing abrasion. (b) FFT spectrum of the engine with valve push rod abrasion.

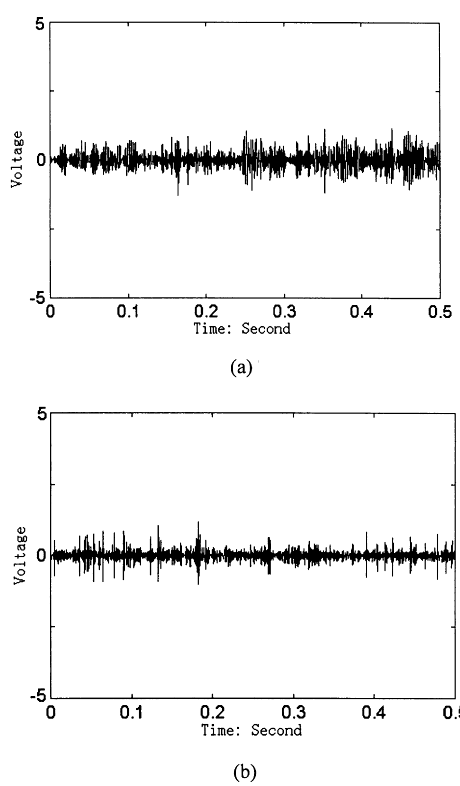

Fig. 7. (a) The purified signal of the engine with crankshaft bearing abrasion. (b) The purified signal with valve rod abrasion.

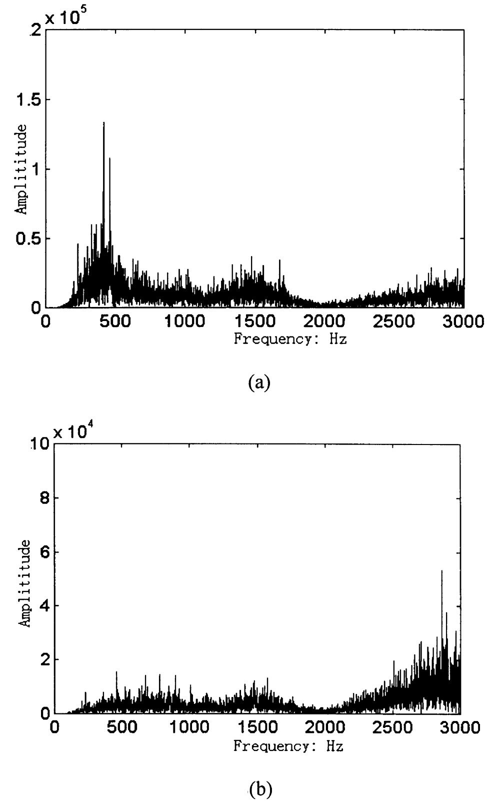

Fig. 8. (a) Purified FFT spectrum of the engine with crankshaft bearing abrasion. (b) Purified FFT spectrum of the engine with valve push rod abrasion.

whomp. The rhythm and timbre of the sounds are rather different and this can be explained using their FFT spectra. The FFT spectra of the purified signals are illustrated in Fig. 8(a) and (b). The distributions of the two spectra are distinctly different. The main difference is that they have different resonant frequencies.

The reason for the difference can be summed up in two points. First, the clearance of the conjugate surface becomes large. With the crank rotating periodically and the piston moving reciprocally, the conjugate parts collide periodically. Then the rhythm of the sound appears. Second, the resonant frequencies of the parts can be excited by instantaneous collision. Different parts have different resonant frequencies. The resonant frequency of each part depends on its rigidity and mass. Thus, the failures occurring in the different parts will produce different frequency components in the spectra, and their sounds will have different timbres. The resonant frequency corresponding to the crankshaft bearing abrasion is about 500 Hz, and the one corresponding to the valve rod abrasion is about 2800 Hz. When the signals are purified, these resonant frequencies are exposed, as shown in Fig. 8(a) and (b).

It should be pointed out that the sampling frequency is not high so that the resonant frequency is not exposed entirely. Because it does not affect the qualitative evaluation, the signal obtained by this sampling frequency is still used.

5. Conclusions

Machine sound varies depending on the condition of the machine. But usually the feature sound is immersed in background noise and is hard to capture. CWT can be used for discovering the signal components relevant to the selected wavelet bases. Then, using a proper basic wavelet, we can obtain the feature components of a signal by reconstructing the wavelet coefficients. The machine sound can be purified in this way. The purified sound can give us a guide on how to pick out the feature sound from the noisy machinery sound. At the same time, the purified sound can help the operators to diagnose the machine correctly, even if the machine sound has a very low SNR.

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