Ultrasonic flaw detection spectrogram characterization of vermicular graphite cast iron engine cylinder head

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Abstract. The defects formed in the manufacture of the vermicular graphite cast iron engine cylinder head seriously affect the operation of the engine, which is necessary to detect. Ultrasonic testing is a non-destructive testing method that has the advantages of quick response, high resolution, and high security. In this paper, various types of specimens are prepared corresponding to different types of actual defects in the vermicular iron cylinder head. An ultrasonic A-scan system was built to test the specimens. The short-time Fourier transform, the continuous wavelet transform, the empirical wavelet transform, and the empirical modal decomposition were adopted to transform the signals into spectrograms which were further analyzed to reveal the inherent features of defects. The results show that the short-time Fourier transform can be used to distinguish all the common defects comparing to other methods. Comparing to the time-domain waveforms, the transformed spectrograms provide clear time-frequency distribution and highlight the inherent characteristics of the signal.

1. Introduction
The automobile engine is an important component of the vehicle, whose quality of cylinder head directly affects the car's reliability. In the manufacture of the cylinder head, the vermicular cast iron is commonly used because of its excellent mechanical properties such as high tensile strength and fatigue strength, as well as good casting and machining characteristics [1]. Influenced by the process, human and other factors, defects such as the hole, loose and shrinkage often occur during the casting of the cylinder head, therefore it is very important to detect it to ensure the reliability of the engine. Currently, methods of detecting vermicular graphite iron castings include non-destructive testing and destructive testing. The destructive method destroys the samples that randomly selected and uses the metallographic observation method to detect the internal defects of the sample. This method has the advantages of accurate detection and intuitive results. However, the sampling process of the destructive test may miss defects, and the destruction of samples causes waste. Compared with destructive testing, non-destructive testing can detect the sample without destroying it, and is widely used in industrial production detection. Common non-destructive testing methods include penetrant testing, radiography testing, eddy current testing, and ultrasonic testing. Based on the principle of...
capillarity, penetrant testing is used to check the surface opening defects. By using the eddy current testing principle of electromagnetic induction, measure the variation of induced eddy current in the workpiece to achieve damage detection and material property evaluation. Penetrant testing and eddy current testing are usually applied to detect the surface defect of samples, but not to reflect the internal defects [2]. Radiography testing realizes detection by emitting uniform intensity rays to the sample and detecting the difference in transmission energy attenuation caused by the internal sample structure, which has the advantages of defecting specimen interior intuitively and accurately. But there are usually the characteristics of high cost and the ionizing radiation harm. Ultrasonic testing transmits ultrasonic waves to the component surface through the coupling medium with the probe and uses the time difference between different reflected signals collected by the probe to realize detection. The height and location of the echo signal can demonstrate the defect properties. Ultrasonic testing can check the internal defects of components and has the advantages of high resolution and safety. However, the structure of the vermicular iron cylinder head is complex, and its internal grain distribution is loose with irregular size, which will affect the ultrasonic propagation speed and attenuation [3], resulting in the decrease of detection quality. Besides, the original signal is abstract, which makes it difficult to manually distinguish the material defect characteristics. Therefore, it is usually to construct a characteristic spectrogram of the detection signal to characterize the sample defect visually.

Time-frequency analysis is an important method to construct the signal characteristics spectrogram, which can reveal the inherent characteristics of the signal and ensures the information integrity through the joint analysis in the time and frequency domain [4]. For example, the short-time Fourier Transform (STFT) makes up for the time-frequency characteristics which cannot be expressed by traditional Fourier transform; the Continuous Wavelet Transform (CWT) realizes the characteristics of multi-resolution analysis by introducing translation and expansion factors to analysis signals at multi-scale [5]; the Empirical Wavelet Transform (EWT) has better adaptability, simple calculation process, faster decomposition speed and strong robustness, which can avoid mode mixing [6]; the Empirical Mode Decomposition (EMD) method can be applied to the decomposition of any signal type to process non-stationary and nonlinear data [7].

Different samples with defects were prepared in the research to solve the detection problem of the vermicular graphite cast iron engine cylinder head by constructing an ultrasonic A-scan detection system. Then process the ultrasonic echo signal with STFT, CWT, EWT, and EMD separately to characterize the defect with spectrograms. Differences among the spectrograms obtained by comparing different algorithms lead to the results of the most suitable signal characterization methods for different defects, thereby achieving abstract analysis of defect ultrasound signal.

2. Experimental design

2.1. Sample Preparation

Vermicular graphite cast iron automobile engine cylinder head is shown in figure 1.

![Figure 1. Sectional view of the engine.](image)
The cut engine head sample with a complex internal structure is shown in figure 2. The shaped structure causes the ultrasonic echo signal propagation so complex that the defect signal will be doped with a lot of clutter, affecting the analysis of the signal.

Samples with the three defects, including hole defects, shrinkage defects, and loose defects, were prepared to restore the actual production to a large extent. The samples are shown in figure 3. And, the hole defects can be divided into single hole defects and porosity defects.

Figure 2. Internal defects of samples. (a) Hole defect; (b) Loose defect; (c) Shrinkage defect.

Figure 3. Test samples for different defect types. (a) Single hole defect test samples; (b) Porous defect test samples; (c) Shrinkage and loose defect test samples.

The single hole sample has 30mm×35mm end face size, 60mm height, and the hole is 30mm away from end face, with 10mm diameter; the porous sample end face size is 30mm×35mm, with 40mm height and six 6-mm-diameter holes that randomly distributed in the sample; the shrinkage and loose samples are both 100mm in height and 60mm in diameter, and the defect is 10mm from the end surface.

2.2. Experimental system
An ultrasonic pulse-echo test system consisting of an arbitrary function generator, power amplifier, oscilloscope, computer and cylinder head casting was built, as a schematic diagram of the experimental system is shown in figure 4. The 1.25MHz single normal probe was used while the arbitrary function generator produced ultrasonic signals, then the power amplifier amplified signals and displayed them in the oscilloscope, and the PC analyzed and processed the collected signals finally.

3. Ultrasonic signal processing algorithm
The samples detection signals were collected with the ultrasonic A-scan experimental system and processed by STFT, CWT, EWT, and EMD respectively to obtain characteristic spectrograms. The signal processing flow chart is shown in figure 5. Ultrasonic A-scan is a point-to-point scan, it obtains one-dimensional data that illustrates the test object performance and information along a specific sound path. Ultrasonic waves will be reflected when they encounter obstacles in the medium and the received signals are processed into waveform images.
3.1. Short-time Fourier transform.
Short-time Fourier transform is a typical linear time-frequency representation method, using the time-frequency joint function to represent the signal. The short-time Fourier transform of the continuous original signal $x(t)$ is shown in equation (1).

$$STFT(t, f) = \int_{-\infty}^{+\infty} x(t) \omega(t - \tau) e^{-j2\pi ft} d\tau$$  \hspace{1cm} (1)$$

where $x(t)$ is the time-domain signal, $\omega(T - \tau)$ is the windowed function, and $\tau$ is the center of the windowed function. STFT is to perform Fourier transform on the part of the window function $\omega(T - \tau)$ intercepting signal $x(t)$. To adjust the position of the window function by changing the parameters of time, resulting in a time-series conversion result argument [8].
3.2. Continuous wavelet transform

Let \( w(t) \in L^2(\mathbb{R}) \), \( W(\omega) \) is the Fourier transform of \( w(t) \), if \( W(\omega) \) satisfies 
\[
C_w = \int_{-\infty}^{+\infty} |W(\omega)|^2 d\omega < \infty,
\]
then \( C_w \) is bounded and \( w(t) \) can be a mother wavelet. The continuous wavelet transform of the 
mother wavelet \( w(t) \) can be defined as follow.

\[
CWT_w(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} s(t) \overline{w\left(\frac{t-b}{a}\right)} \, dt
\]  

(2)

where \( a \) is the expansion factor; \( b \) is the translation factor; \( s(t) \) is the time-domain signal; \( \overline{w} \) is the 
\( w \) conjugate, \( w_{a,b}(t) = \frac{1}{\sqrt{a}} w\left(\frac{t-b}{a}\right) \) is the wavelet sequence of mother wavelet after time translation 
and scale expansion transformation [9]. Complex Morlet is selected for the wavelet basis.

3.3. Empirical wavelet transform

EWT is adaptively divided following the Fourier spectrum of the original signal to construct an 
empirical wavelet, based on Meyer orthogonal wavelet. Appropriate boundaries were selected 
to construct a band-pass filter to extract the natural modes in each interval, and performed the component 
of mode with Hilbert transform, obtain each component of the instantaneous frequency and amplitude. 
The signal \( f(t) \) can be decomposed into \( N+1 \) functions, expressed as:

\[
f(t) = \sum_{k=0}^{N} f_k(t)
\]  

(3)

Let \( f_k(t) = F_k(t) \cos (\varphi_k(t)) \). The angular frequency of the signal is \( \omega \) \( (\omega \in [0, \pi]) \) in 
the frequency domain. Decompose \([0, \pi]\) into \( N \) different bandwidths intervals shown as \( A_n \), each segment is 
expressed as:

\[
A_n = [\omega_{n-1}, \omega_n], n = 1, 2, \ldots, N
\]  

(4)

\[
U_n^{N} A_n = [0, \pi]
\]  

(5)

Define \( T_n = 2\pi n \), centered on \( \omega_n \). The empirical scaling function \( \hat{\varphi}_n(\omega) \) and the empirical wavelet function \( \hat{\psi}_n(\omega) \) can be expressed as follows.

\[
\hat{\varphi}_n(\omega) = \begin{cases} 
1; & |\omega| \leq (1 - \gamma) \omega_n \\
\cos \left[ \frac{\pi}{2} \beta \left( \frac{1}{2 \gamma \omega_n} |\omega| - (1 - \gamma) \omega_n \right) \right] ; & (1 - \gamma) \omega_n \leq |\omega| \leq (1 + \gamma) \omega_n \\
0; & \text{otherwise}
\end{cases}
\]

(6)

\[
\hat{\psi}_n(\omega) = \begin{cases} 
1; & (1 + \gamma) \omega_n \leq |\omega| \leq (1 - \gamma) \omega_{n+1} \\
\cos \left[ \frac{\pi}{2} \beta \left( \frac{1}{2 \gamma \omega_{n+1}} |\omega| - (1 - \gamma) \omega_{n+1} \right) \right] ; & |\omega| \leq (1 + \gamma) \omega_{n+1} \\
\sin \left[ \frac{\pi}{2} \beta \left( \frac{1}{2 \gamma \omega_n} |\omega| - (1 - \gamma) \omega_n \right) \right] ; & (1 - \gamma) \omega_n \leq |\omega| \leq (1 + \gamma) \omega_n \\
0; & \text{otherwise}
\end{cases}
\]

(7)

where \( \beta(x) = x^4(35 - 84x + 70x^2 - 20x^3); 0 < \gamma < 1 \) while \( \gamma < \min_{\tau_n}(\omega_{n+1} - \omega_n)/\omega_n) \); \( \tau_n = \omega_n \).
Be similar to traditional wavelet, detail coefficients and approximation coefficients obtained by the following formula:

\[ W_f^x(n, t) = \int f(\tau) \psi_n(\tau - t) d\tau = (f(\omega)\overline{\psi}_n(\omega))^\vee \]  \hspace{1cm} (8)

\[ W_f^x(0, t) = \int f(\tau) \Omega_1(\tau - t) d\tau = (f(\omega)\overline{\Phi}_1(\omega))^\vee \]  \hspace{1cm} (9)

Restructure the signal with \( W_f^x(n, t) \) and \( W_f^x(0, t) \), shown as:

\[ f(t) = W_f^x(0, t) * \Omega_1(t) + \sum_{n=1}^{N} W_f^x(n, t) * \psi_n(t) \]

\[ = \left[ W_f^x(0, \omega) * \overline{\Omega}_1(t) + \sum_{n=1}^{N} W_f^x(n, \omega) * \overline{\psi}_n(t) \right]^\vee \]  \hspace{1cm} (10)

where \(^\wedge\) is Fourier transform, \(^\vee\) is inverse Fourier transform, - is conjugate, and * is convolution [10].

Thus, the signal \( f(t) \) is decomposed into an approximation component \( f_0(t) \) and \( N-1 \) detail components \( f_k(t) \), \( (k=1,2,\cdots,N−1) \), defined as:

\[ f_0(t) = W_f^x(0, t) * \Omega_1(t) \]  \hspace{1cm} (11)

\[ f_k(t) = W_f^x(k, t) * \psi_k(t) \]  \hspace{1cm} (12)

### 3.4. Empirical mode decomposition

Empirical mode decomposition may be achieved by the time scale features of data to obtain the intrinsic fluctuation pattern and decompose ultrasonic A-scan signal into a series of intrinsic mode function (IMF) without any base functions in advance [11].

The flow chart of EMD is shown in figure 6.

![Flow chart of EMD](image)

**Figure 6.** The EMD flow chart.

After decomposing a series of IMF components, the original signal can be expressed as:
\[ x(t) = \sum_{i=1}^{n} imf_i(t) + r_n(t) \]  

where \( imf_i(t) \) is the IMF component, and \( r_n(t) \) is the residual component.

4. Results and Discussion

4.1. Analysis of defect original echo signal

The ultrasonic A-scan pulse-echo experiment with the experimental system illustrated in Subsection 2.2 was performed on the sample in figure 3 to obtain sample echo signals, as shown in figure 7.

The abscissa in the figure represents time, and the ordinate represents the amplitude of the echo signal. Figure 7(a) shows the waveform of the specimen, which is utilized as a reference signal in the analysis of other waveforms to identify defects. Figure 7(c) demonstrates the waveform of the porous defect specimen. In which, the first echo is the reflection defect signal of the hole closer to the end surface while the second echo corresponds to the second hole. The signal in figures 7(b) and 7(c) have similar waveform shapes. Therefore the way that identifying the defects manually is easily affected by the operator’s mistakes. The energy of the echo signal in figure 7(d) is lower than that in figure 7(a). because that the loose defect attenuates the echo signal. The echo signal in figure 7(d) has a higher amplitude than that in figure 7(e). Accordingly, the defect size in porous defects is smaller and the volumetric density is lower compared with the shrinkage defects. The waveform of the signal in figures 7(d) and 7(e) are similar. Therefore the difficulty of defect identification will arise when an alternative defect appears.

![Figure 7](image_url)

**Figure 7.** Original signal waveform of ultrasonic testing. (a) Normal signal; (b) Single hole defect; (c) Porous defect; (d) Loose defect; (e) Shrinkage defect.

The spectrogram is the visual representation of light, sound, or other signals, which changes with time or other variables. In the following paper, algorithms will be used to process the detection signals in each sample to construct spectrograms to reflect the defect characteristics.

4.2. STFT spectrogram analysis of ultrasound signal

STFT was used to obtain the signal spectrogram as shown in figure 8.
Figure 8. STFT spectrogram with normal signal and four defect signals. (a) Normal signal; (b) Single hole defect; (c) Porous defect; (d) Loose defect; (e) Shrinkage defect.

In figures 8(a) to 8(e), signals with higher energy appear near time 0. Due to single hole and porous defects, the sound waves are scattered and the wave packets are aliased. The energy distribution of figures 8(b) and 8(c) is distorted compared to figure 8(a), so the hole-type defects can be distinguished. The echo energy exists in figure 8(b) only is used to distinguish from figure 8(c). It also shows that the sound waves attenuate more when passing through porous defects. The initial crosstalk signals in figures 8(a), 8(d) and 8(e) are similar, but there are multiple echo energies in the STFT spectrogram of loose and shrinkage defects [12], which is different from the normal spectrogram. Meanwhile, figure 8(e) has smaller energy and lower amplitude than figure 8(d). Both figures 8(e) and 8(d) have different echo energy position distribution, so shrinkage defects can be clearly distinguished from loose defects. Meanwhile, figure 8(d) has smaller echo energy and amplitude than that of figure 8(e), and the energy distribution between them is also different. Shrinkage defects may thus be significantly distinguished from loose defects.

4.3. CWT spectrogram analysis of ultrasound signal

The time-frequency diagrams were obtained by processing each group of signals with CWT. Figure 9 shows the CWT spectrograms of the normal signal and four defect signals.
The five signal energies are all high at 0ms affected by crosstalk, and then show different changes over time. The energy in figures 9(d) and 9(e) is lower than that in figure 9(a), indicating that the porosity and shrinkage defects have a significant impact on the sound wave attenuation. But the similarity of the spectrogram characteristics in figures 9(a), 9(d) and 9(e) brings out the difficulty in distinguishing the defects of porosity and shrinkage [13]. Although the signal energy in figures 9(b) and 9(c) are almost distributed in the same frequency range as that of figure 9(a), there is a mixture of multiple packets that is different from figure 9(a), which can clearly distinguish the hole type defects. However, it is also difficult to distinguish between a single hole and porous defects since no obvious difference is found between figures 9(b) and 9(c).

4.4. EWT and EMD spectrogram analysis of ultrasound signal
The signal was processed to obtain the empirical wavelet spectrogram and empirical mode spectrogram of normal area signal and defect signal, as shown in figure 10.

Figure 9. CWT spectrogram of normal signal and four defect signals. (a) Normal signal; (b) Single hole defect; (c) Porous defect; (d) Loose defect; (e) Shrinkage defect.
Draw the time-domain waveform corresponding to the signal above the spectrogram to reflect the time correspondence between signal amplitude and frequency. The signal energy in the figures 10(a1), 10(a2), 10(d1), 10(d2), 10(e1) and 10(e2) reaches the maximum corresponding to the maximum amplitude in the time-domain waveform when time tends to 0.4 ms. About 1.7 ms, another energy peak appears in the spectrogram corresponding to the time-domain waveform. The signal energy is mainly concentrated in the frequency range of 20 to 40 in the figures 10(a2), 10(d2) and 10(e2), but has lower energy and more scattered distribution in their respective EWT spectrograms. So that its observation and analysis are difficult. Therefore EWT spectrogram recognition of these three cases to be significantly better than the EMD. The energy in the EWT diagrams of the single hole and porous defects are mainly within the frequency range of 0 to 10, lower than those without the defect signal, meanwhile the signal energy is low[14]. The defects such as holes attenuate waves more. Besides, the difference between loose, shrinkage defects and normal signal spectrogram is small, indicating that the influence of wave propagation affected by loose and shrinkage defects is small. Overall, the EWT spectrogram is more recognizable than that of EMD, which is conducive to signal analysis. These two methods are identified defects belonging to holes or other classes but would like to determine the specific defect which is still present certain difficulties.

5. Conclusion
Through the establishment of the ultrasonic A-scan system, the four defects consist of the single hole, porous, loose, and shrinkage in the prepared vermicular graphite cast iron engine cylinder head samples were detected. Accomplished analysis of defect characteristics with spectrogram obtained from defect signals that were processed separately by STFT, CWT, EWT, and EMD. The main conclusions are as follows:

(1) Compared to the time-domain waveform obtained by conventional ultrasonic testing, characteristic spectrograms have a better performance in distinguishing the single hole, porous, porosity and shrinkage defects. STFT signal characteristics of each defect can distinguish them very well. CWT is sensitive to hole defects but cannot distinguish the loose and shrinkage defects. EWT is more suitable than EMD to characterize defects by spectrogram overall, but it is only able to show the difference of defects characteristics between holes class and loose shrinkage class, not further differentiate the specific type of defects.

(2) It is easy to distinguish holes class and loose shrinkage class defects, but further refinement requires specific methods; the attenuation effect of hole defects is more obvious; the influence of loose and shrinkage defects on ultrasonic wave propagation is smaller than that of holes. Compared with the time-domain waveform, the characteristic spectrogram can show the time-frequency distribution of the signal and highlight the inherent characteristics of the signal.

(3) Future research on the detection of cylinder head defects in vermicular graphite cast iron engines will focus on combining inspection techniques with artificial intelligence, as traditional inspection techniques are not sufficiently accurate and efficient. The use of artificial intelligence
technology to analyze the established sample library of ultrasonic detection signals can obtain high-level abstract features of the signals and achieve intelligent defect detection.

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