Research of Daubechies Wavelet spectrum of vibroacoustic signals for diagnostic of diesel engines of combine harvesters

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Abstract. The authors have researched the practice of diesel engines vibration diagnostics of combine harvesters and established the existence of non-stationary signals dissemination, whose statistical properties evolve over time. It was determined that they consist of short-term high-frequency elements, which are supported by low-frequency components are imposed on the first. The short-term Fourier transform was used to analysis such signals, which showed the appropriateness of the frequency distribution in concert with the differ time allocation. The authors have used the wavelets in cases where the certain signal analysis result should contain not only a simple enumeration of its typical frequencies, scales (spectrum analysis), but also local coordinates data under which these frequencies manifest themselves. This is an issue to identify the aspects when defects in the diesel engines of combine harvester’s connections arise.

1. Introduction

Fourier transform is the most widely used in vibration diagnostics of diesel for spectral analysis [1]. It decomposes the signal into orthogonal basis functions (sines and cosines), determining its constituent frequencies [2]. This method is strictly mathematically being appropriate for stationary signals (bearings, turbines) and improper for non-stationary signals (piston transfer, gas distribution mechanism, nozzles, etc.) [3]. Particularly, the Fourier transform does not make it possible, for example, to determine either a certain frequency was in a signal at all times or it appeared there at a given time (a defect occurrence) [4]. At present, all vibroacoustic signals, even non-stationary with a certain approximation, are considered as stationary, dividing them into blocks of conditionally stationary segments [5], the statistics of which is constant at its passage over a period of time. In accordance with the vibrodiagnostics practice, non-stationary signals, the statistical properties of which change over time, are most commonly available [6].

Commonly, they consist of short-term high-frequency elements [7], accompanied by low-frequency components superimposed on the former [8]. Such a method should be used to analyse those signals, should show good frequency distribution along with excellent time distribution [9].

The first is to localize the low frequency components and the second is to allow the high frequency components [10]. This method [11] is found in the literature for the analysis of non-stationary signals and is called the Short-time Fourier transform (Short-time Fourier transform (STFT) (figure 1).
2. Materials and methods
The time interval of the signal is divided into segments and converted by STFT, using it separately for each segment [12]. Thus, the transition to the time-frequency (frequency-coordinate) signal display is occurred, in which signal is considered fixed within each segment (window) [13]. The window converting result is a family of spectra that characterizes the change of signal spectrum in the intervals of the window shift transformation [14]. Briefly, STFT can be characterized by the following algorithm: define an analysis window (e.g., a 30 ms narrowband, 5 ms broadband); determine the overlap magnitude between windows (e.g. 30%); select a window function (e.g., Hann, Gauss, Blackman); create a window segment (signal multiplication by the window function); employ a fast Fourier transform (FFT) to each window segment [15].

![Figure 1. Schematic algorithm of STFT analysis.](image1)

3. Results and discussion
The obtained by this algorithm spectra of segments make it possible to select and analyze the features of the non-stationary signal on the coordinate axis. Normally the size of the carrier of the window function $w(t)$ should be established according to the stationarity interval of the signal.

For instance, let examine the following transformation for a real vibroacoustic signal (figure 2) obtained from the cylinder block of the engine SMD-31A by the accelerometer B&K Type 4333 No 272437 installed in the 3rd cylinder piston transfer zone.

![Figure 2. Vibroacoustic signal of the internal combustion engine and its arrangement on the windows of transformation.](image2)

Window conversion is defined by the formula:

$$S(w,b) = \int_{-\infty}^{\infty} s(t) \cdot w(t - b) \exp(-j\omega t) dt,$$  \hspace{1cm} (1)
The \( w(t-b) \) function is a function of the window shift transformation in the coordinate \( t \), where parameter \( b \) specifies fixed shift values. In a windows shifting with an equable domain \( b \), the \( k\Delta b \) are assumed to be equal. As the conversion window can be used both the simplest rectangular window and special weight windows (Blackman, Bartlett, Gauss, etc.), which provide small distortions of the spectrum at cutting window segments of signals. Listing of the window conversion example for a non-stationary vibration signal and the result is shown (2) and figure 3.

\[
wb(k,n) := \begin{cases} 
0.42 - 0.5 \cdot \cos \left( \frac{2 \cdot \pi \cdot k - n}{k - 1} \right) & \text{if } k \neq 0 \\
0 & \text{otherwise}
\end{cases}, \quad N = 1.638 \times 10^4 \quad \Delta b := 128
\]

\( w := 127 \quad n := 0...N \). \( S := \text{cfft}(M^{(0)}) \quad SQ := (M^{(0)}) \quad \Delta \omega S := \frac{2 \pi}{\text{Discr} + 1} \)

\[
\Delta \omega S := \frac{2 \pi}{w + 1} \Delta \omega S = 3.835 \times 10^{-4}
\]

\[
w(s,N,\Delta b,w) := \begin{cases} 
k \leftarrow 0 & 
\text{for } b \in 0...\Delta b, N-w \\
k \leftarrow k + 1 & 
\text{for } b \in 0...b + w \\
y_{n-b} \leftarrow s_n \cdot wb(n + 1, w + 1) & 
S_w \leftarrow \text{CCFT}_{(y)} \\
\text{for } n \in 0...w & 
S_{k,n} \leftarrow S_w \\
S &
\end{cases}
\]

\( S_w := N^{-1} \cdot \Delta b \cdot w \cdot (SQ, N, \Delta b, w) \).

(2)

**Figure 3.** Implementation of window conversion using two types of windows.
According to the spectrum of the signal S it is possible to speak about presence of its harmonic oscillations at more than 6 strongly pronounced frequencies, determine the relationship between the amplitudes of these oscillations and indicate the locality of oscillations in the signal interval. Coordinate resolution of window conversion is determined by the width of the window function and inversely proportional to the frequency resolution. The functional capabilities of the short-time Fourier transform limit the ability to analyse the spectral composition of signals at an interval that is the same for all frequencies, particularly, the frequency resolution is the same for the entire frequency range.

Relating to the processing of complex signals. Of course, the vibration signals of the internal combustion engine are also related, the problem of short-term window transformation is that have to choose the window size “once and for all”, to analyses the whole signal. However, different parts of the recorded signal may require the use of particular duration windows. For example, if the signal consists of far-distant frequency components, thus it is possible to contribute the frequency resolution in favour of temporary, and vice versa. Thus, due to using fixed-width windows, the STFT is not always appropriate for analyzing low and high frequency signals at the same time (piston transfer signal, nozzle, timing mechanism). Such an analysis is made possible by using a flexible window which becomes narrow as it passes through the high-frequency signal component and turns wide in passing the low-frequency signal region. The wavelet analysis of signals based on the wavelet transform makes this possible. Wavelet signal transform is the signals decomposition into components by a particular function called wavelet. Wavelets have become a necessary mathematical tool in a number of studies. They are used in cases where the result of the analysis of a certain signal should contain not only a simple list of its characteristic frequencies, scales (spectral analysis), but also information about some local coordinates at which these frequencies manifest themselves. This is precisely the task when it is necessary to define the moments when defects in ICE junctions arise. The general principle of basis wavelet transform construction is to use large-scale changing and offset. The wavelet basis is a function defined as $\Psi(t-b)a^{-d}$, where $b$ is the offset, and $a$ is the scale. Besides to become wavelet, the function must have a zero square and what is more zero the first, second and other points. The Fourier transform of such functions equals zero at $w=0$ and looks like a bandpass filter. For different values of $a$, it will be a set (block) of bandpass filters. In the wavelet spectra of the vibration signal estimation in a discrete form, the sampling rate (step) of the parameters $b$ and $a$ is essential for the demonstrativeness and clarity of the spectrum. The sampling step $\Delta b$ is usually taken to be equal $\Delta b$ signals being analysed, equal to 1, meanwhile the time scale of the wavelet spectrum corresponding to the time scale of the signal and convenient for localization of the signal features. To enable the basic wavelet size changing, a constant scale index $d$ is introduced into its formula (figure 4).

$$\Psi(t,a,b,d) = \frac{1}{\sqrt{a} \cdot d} \left[1-2\left(\frac{t-b}{a \cdot d}\right)^2\right] \cdot \exp\left(-\frac{(t-b)^2}{a \cdot d}\right),$$ (3)

![Figure 4. Changing the base size of the Wavelet function derivative of Gauss function.](image)

For instance, let's try to make a wavelet transform in MathCad system using the fourth order db4 Daubechies Wavelet input the functions of direct $S:=\text{wave}(s)$ and inverse $s:=\text{iwave}(S)$ transformation.
To visualize a picture of the coefficients, the submatrix is converted into a two-dimensional array, bringing the input signal to a single numerical axis (figure 5) (stretching the coefficients along the offset axis without changing their value). Due to the wavelet transform dyad, the expressiveness of the wavelet spectrum preserves all frequency temporal features of the signals and what is more significantly, allows to change (certain processing) the signal at different levels of decomposition, and after processing to implement the reversed wavelet transform without loss of information.

\[ U_r := \text{ceil} \left( \ln(j) \cdot \ln(2)^{-1} \right) = \text{ceil} \left( \ln(16380) \cdot \ln(2)^{-1} \right) = 14, \]  

where: \( j \) – is the number of counting (points) of the recorded vibration signal.

Wavelet spectrum data vector \( TP := \text{wave}(M^{(0)}) \) \( G := 12 \ r := 0..G \ A_{r,j} := TP \ \text{floor} \left( \frac{j \cdot 2^{G-r}}{2^G + 1} \right). \)

![Figure 5. The Daubechies wavelets spectrum (right – interpolated form).](image)

These seven are the most informative, although the total amount may be larger. It is possible to display the wavelet spectrum in 2D and 3D form (figure 6). The main purpose of the article is to show the possibility of using wavelets to clearing the vibroacoustic signal from the noise, which is usually attributed to other sources of oscillation. During the CNG diagnostics signals from the fuel equipment, gas distribution mechanism, etc. can serve as noise. Classic filtration can be used for cleaning, but a wavelet cleaning is the best option. Some calculations are needed to begin this purge. To prepare the wavelet transform, the number of levels complete decomposition of the signal \( M \) is determined and the array is supplemented by zeros to the necessary \( 2M \) value.
In the dyadic separation of the spectrum at each decomposition level, the first level of detail coefficients will be formed from the high-frequency part of the signal spectrum from $\pi/2$ to $\pi$ (in a one-sided physical frequency scale). The second part of the spectrum from 0 to $\pi/2$ is converted to approximating coefficients. At the second level, the approximating coefficients are again split in half, converting the range $\pi/4-\pi/2$ into detailing, and the range $0-\pi/4$ into approximating coefficients of the second decomposition level, and thus on to the full decomposition (in this case 14 times). This permits the approximately noise limit to be set directly over the frequency spectrum of the signal, and according to the decomposition levels in which the noise power is close to and higher than the signal power. When forming a new line level, coefficients that exceed the established thresholds $ub := -3\sigma$ and $ut := +3\sigma$ of noise distribution, it is advisable to store completely with a slight decrease in values. After the new decomposition line is formed (figure 7), it is possible to replace the corresponding decomposition level in the full array of coefficients and visually evaluate the result by analyzing the input and output of a certain decomposition level signals. After inverted wavelet conversion, the received signal contains both the values of the eigenvalues and the values of the wavelet coefficients. In other words, it receives synthesis (mixed signal). By conducting a fast Fourier transform, it is possible to compare the spectra of the pure (input-green) and synthesized noise-purified (output-red) spectra (figure 8).

*Figure 7. The fourth level decomposition of the wavelet transform.*

*Figure 8. Spectra before and after wavelet transform and noise spectrum.*

It can be seen wavelet cleaning has retained characteristic peaks throughout the frequency range, which form periodic jumps of the signal values that virtually no linear frequency filter can perform. However, using the wavelet cleaning after signal wavelet noise from linear filters is quite perspective in terms of signal separation (figure 9). The using Butterworth linear bandpass filter of 6th order (figure 9) even permits you to visually evaluate the result of the wavelet cleaning of the signal.
The signal after filtration is well separated and can easily be used for an automated diagnostic system. The main problem of such a software complex is the wavelet form choosing, the choice of decomposition levels, which, after some research, may underlie the development of an appropriate automated software complex vibroacoustic diagnosis of ICE.

4. Conclusions
The use of the Dobeshi wavelet spectra and the Fourier window transform for the analysis of the vibroacoustic signal makes it possible to recognize changes in the state of the engine mechanisms and the location of the source of the change itself. The decomposition of the signal by all decomposition equations makes it possible to find the level, at which the signal is less than the noise, through approximating coefficients that exceed the set thresholds $ub := -3\sigma$ and $ut := +3\sigma$ noise distribution.

This study established the 5th level of decomposition in applied nature of vibration diagnostics of the combine engine. It is proved that the value of the constant scale factor should be in range $d = 2..1.0$.

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