

## Fault Diagnosis: Spectral Analysis of the Vibration Signals in Transfer Press

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### Abstract

Fault diagnosis using vibration signals is a major challenge for industrial manufacturing. Obtaining defect information is an important step to make decisions about the maintenance in prognostic and health management systems. Existing studies mostly considers vibration signals collected from elements such as rolling element bearings and hydraulic presses. In this paper, we use the vibration signals obtained from the mechanical transfer press during metal forming process and analyze them from the signal processing point of view. Experimental results reveals that spectral analysis is a good candidate for fault diagnosis and it provides important information about the localized faults embedded in the vibration signals.

**Key words:** Fault Diagnosis, Manufacturing Science, Signal Processing, Intelligent manufacturing

### 1. Introduction

Fault diagnosis is the task of detecting faults occur during metal forming process. It is an important problem since predictive maintenance and quality control are crucial for low cost production. It is also a challenging problem because collecting useful and appropriate data is the fundamental requirement for fault diagnosis. Fault diagnosis using vibration signals obtained from mechanical transfer press in forming process plays a vital role for industrial manufacturing.

There exist several studies focusing on fault diagnosis mostly using vibration data acquired from rotating machinery or rolling-element bearings. For example, it was found by various researchers that envelope analysis is a powerful tool for diagnostics of rolling-element bearing signals [1, 2, 3]. In [1], authors compared cyclostationary and envelope analysis on vibration data for diagnosing of rolling-element bearings and they reported that envelope analysis is advantageous over cyclostationary analysis (spectral correlation). In [2], it was stated that a fault signal consist of two components: (i) deterministic part and (ii) stochastic part. It was reported that deterministic part is diminished by low pass filtering effects. Thus, squared envelope analysis was found to be an important method to overcome this problem [2]. A multiband envelope spectral extraction technique was proposed to tackle with determining optimal frequency band for narrow band demodulation using vibration signals for fault diagnosis in [3]. In previous studies it was observed that envelope spectrum is randomly distributed over the frequency. However, when vibration signal has local faults, envelope spectrum was found to be dominated by the fault characteristics [4, 5]. Vibration signals that have localized faults were treated as cyclostationary [6]. Therefore cyclostationary analysis for fault diagnosis has received great attention and several studies have been reported in literature. Spectral correlation, spectral coherence, spectral kurtosis and kurtogram are the

most widely used cyclostationary analysis techniques for fault diagnosis [6, 7, 8]. Wavelet analysis is another tool successfully applied on vibration data for fault diagnosis and it was observed that wavelet analysis is more efficient than short-term Fourier transform (STFT) for non-stationary transient vibration signals [9, 10].

In this study, we focus on fault diagnosis using vibration signals collected from mechanical transfer press. Although there are few studies previously focused on fault diagnosis using vibration data, data used in these studies obtained from hydraulic press [11]. In this work, the analyses are carried out from signal processing point of view. To this end, spectral analysis, envelope analysis and wavelet packet based analysis are utilized for fault diagnosis.

## 2. Vibration Data Analysis

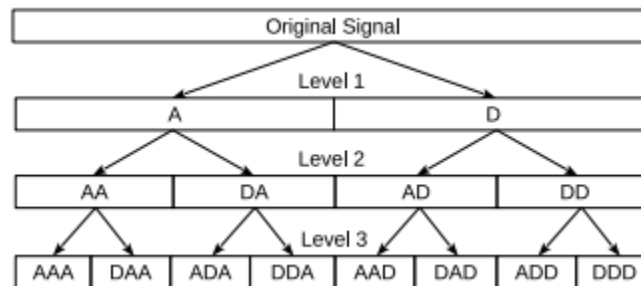
### 2.1. Long Term Average Spectrum

Long-Term Average Spectrum (LTAS) provides information on the spectral distribution of the vibration signal. In the averaging process the short-time variations will be averaged out and resulting spectrum less affected by noise [12]. In many cases, observing the average frequency distribution of a signal's energy would be highly informative. Long term average spectrum (LTAS) provides the spectral information of a signal averaged over time and it is generally used to investigate the persistent spectral features of a signal. LTAS has been successfully used for analysing various types of signals and found very helpful for audio signals in particular [13, 14].

Suppose that  $x[n]$  is the signal that LTAS analysis will be evaluated on. First  $x[n]$  is divided into overlapping blocks where each block consists of  $N$  samples and each block is windowed with a data-tapering window function  $w[n]$ :

$$x[k, n] = \sum_{n=kM}^{kM+N-1} x[n]w[n - kM] \quad (1)$$

where  $M$  is the time shift (samples) between consecutive blocks and  $w[n - kM]$  is the shifted version of the window function  $w[n]$ . In order to compute the LTAS of the signal  $x[n]$ , first the power spectrum of each block  $x[k, n]$  is computed:



**Figure 1.** A three-level Wavelet packet transform used in this study. A: Approximations, D: Details.

$$|X^{(k)}(f)|^2 = \left| \sum_{n=0}^{N-1} x[k, n] e^{-j2\pi f n/N} \right|^2 \quad (2)$$

Where  $f = \{0, 1, \dots, N - 1\}$  is the discrete frequency index and  $k$  is the frame index.  $|X^{(k)}(f)|^2$  is referred to as spectrogram of the signal  $x[n]$  and provides time-frequency variation of a signal [15]. Then LTAS is computed as the logarithmic power spectrum averaged over all blocks:

$$LTAS(f) = \frac{1}{K} \sum_{k=1}^K \log |X^{(k)}(f)|^2 \quad (3)$$

Where  $K$  is the total number of short blocks extracted from  $x[n]$ .

## 2.2. Envelope Analysis

Analytical signal of a signal  $x[n]$  is defined as:

$$x_a[n] = x[n] + jx_h[n] \quad (4)$$

Where  $x_h[n]$  is the Hilbert transform of the  $x[n]$ .

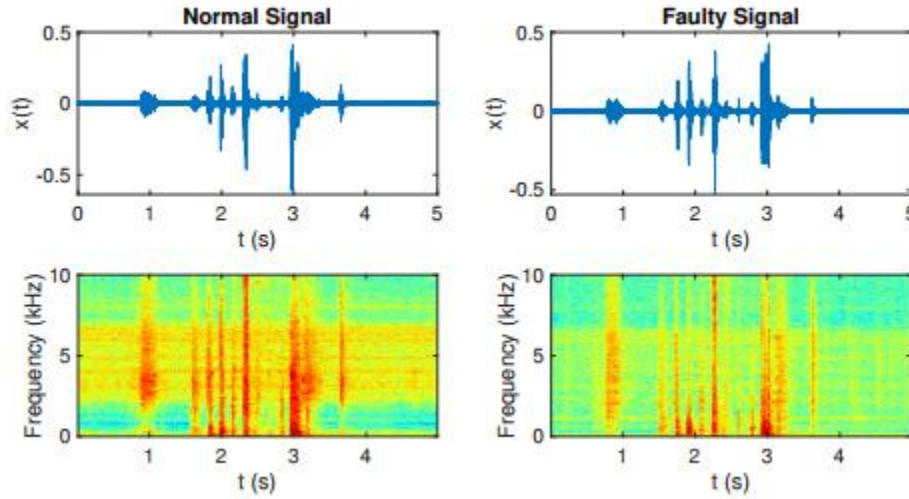
Hilbert transform is widely used to find the envelope of a modulated signal. If original vibration signal  $x[n]$  is assumed to be generated by a modulation process, then the envelope of the modulated signal corresponds to the raw information (message) signal. Therefore, the envelope of the signal  $x[n]$  is computed by the Hilbert transform is defined as:

$$e[n] = |x_a[n]| = \sqrt{x^2[n] + x_a^2[n]} \quad (5)$$

## 2.3. Wavelet Packet Analysis

Wavelet packet transform (WPT) is an extended version of standard wavelet transform (WT). At the first level of classical wavelet transform, the signal is first decomposed into two parts: approximation (A1) and details (D1). The approximation of the signal provides information about the signal's low frequency characteristics whereas details part reveals more detailed information about the signal's high frequency content. At the second level of WT, the approximation part obtained from the previous level is decomposed again into two components which corresponds to approximation (A2) and detail (D2). This process is repeated until the desired number of levels are achieved [16].

WPT in turn, provides a more detailed analysis than WT because WT decomposes only the approximation parts into approximation and details components. However, WPT decomposes both approximation and detail components at each level which results a more detailed analysis and a complete decomposition three. In this study, we use a three-level WPT (see Fig. 1) to analyse the vibration signals for fault diagnosis.



**Figure 2.** Spectrogram of normal and faulty vibration signals consisting of a single hit (case 1).

### 3. Experimental Setup and Results

#### 3.1. Data Description

Vibration data is collected by two identical shear type piezoelectric accelerometer sensors. They are mounted to both horizontal sheet metal forming dies. Vibration signals are sampled at 20 kHz. Experimental analyses are conducted in two different cases:

- **case 1:** Both normal and faulty vibration signals contain single hit of the press.
- **case 2:** Both normal and faulty vibration signals contain multiple consecutive hits of the press.

With this we aim at investigating possible differences between normal and faulty signals and reveal the discriminating information.

#### 3.2. Signal Processing

In the experiments, we process the vibration signals by dividing them into short blocks as described in section 2. While processing the signals, we divide each signal into short frames consisting of 1000 samples (50 ms) and consecutive frames are overlapped by 500 samples (25 ms). Each short block is windowed by a 50 ms Hamming window. In order to transform the time-domain signals into frequency domain, we used 1024 point fast Fourier transform to calculate the discrete Fourier transform of the each block.

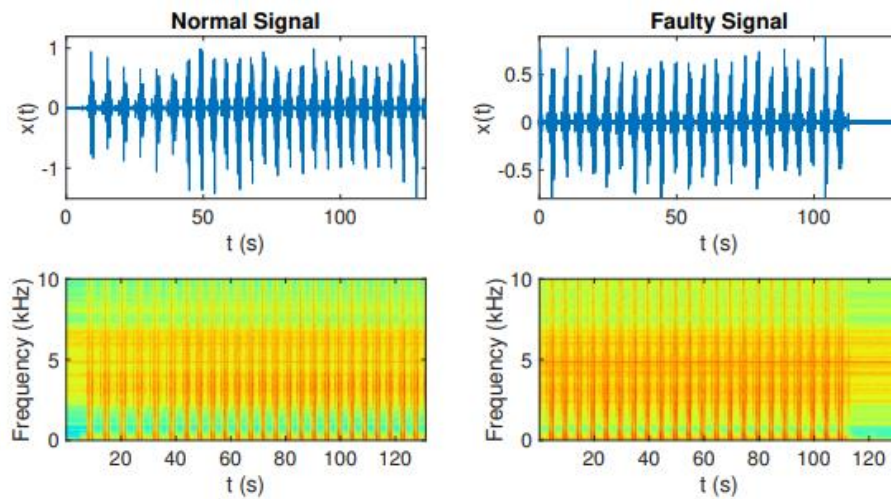
### 3.3. Results

#### 3.3.1. Spectrographic Analysis

In the experiments we first analyse the normal and faulty vibration signals by observing

their spectrograms in order to investigate their behaviours in time-frequency domain. Fig. 2 shows the time domain normal and faulty signals consisting of single transfer press hits with their spectrograms. From figure, we can observe that normal and faulty signals considerably differ in their spectrograms. First, normal vibration signal contains more energy at high frequencies in comparison to faulty signal. Similarly, the energy of the normal signal within the frequency range 2-7 kHz is almost uniformly distributed over time and this is possibly because of the environmental noise. However, the faulty signals contains much less energy within this frequency range.

Next, we analyse the spectrograms of the vibration signals consisting of multiple transfer press hits in order to see whether there exist important differences that does not occur in single hit signals.



**Figure 3.** Spectrogram of normal and faulty vibration signals consisting of a multiple hits (case 2).

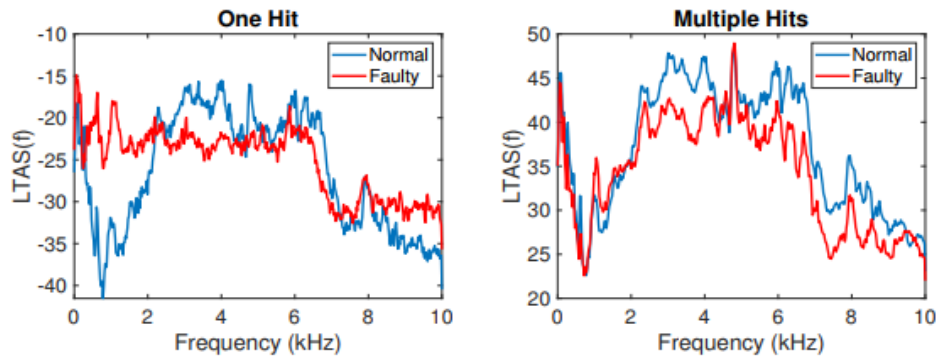
Fig. 3 shows the time domain multiple hit signals and their spectrograms (case 2). From figure, the quasi-periodic behaviours of the both signals (normal and faulty) can easily be seen in time domain signals as well as in spectrograms. One interesting observation from the Fig. 3 is that both normal and faulty signals contains a consistent frequency component at 5 kHz. This probably corresponds to the component which continuously operates at 5 kHz frequency in hydraulic transfer press. In contrast to case 1 (single hit signals – Fig. 2), faulty signal has much more energy at high frequency region.

### 3.3.2. LTAS Analysis

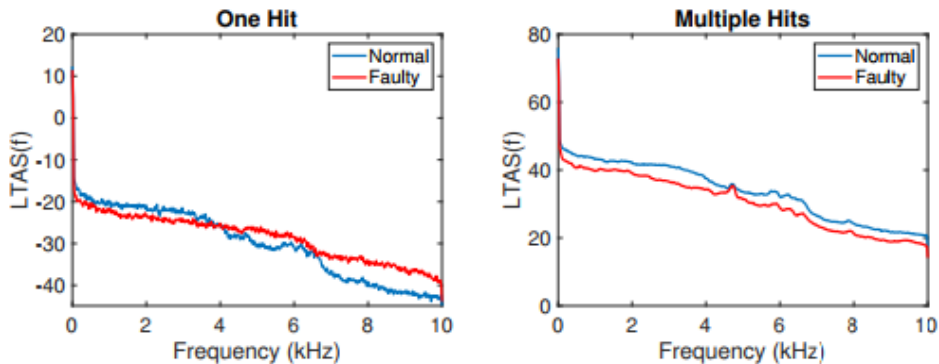
Long-term average spectra (LTAS) for normal and faulty signals for case 1 and case 2 are shown in Fig. 4. When normal and faulty signals consist of single hits, LTAS includes considerable differences in low and high frequency regions. We can observe significant differences in low and high frequency regions. We can observe significant differences from 0 Hz up to 2 kHz and from 8 kHz to 10 kHz between normal and faulty signals consisting of single hits (left figure in Fig. 4). Interestingly, a spectral peak (impulse) occurs at 5 kHz frequency for normal signal whereas it does not exist for faulty signal. However, for signals consisting of multiple hits (case 2), both normal

and faulty signals contains a strong spectral peaks at 5 kHz frequency and they completely matches. Differences between normal and faulty signals in low frequency regions diminish when signals contains multiple press hits.

Next, we analyse the LTAS computed from the envelope signals rather than original signals. In this analysis we assume that original vibration data is generated by a modulation process and therefore envelope signal contains the information signal that is modulated by a carrier. To this end, we first computed the envelope signal as described in section 2.2 and then LTAS of the envelope signal is obtained. Fig 5 shows the LTAS of the envelope signals for single and multiple hits. For the signals with single hits, LTAS of the envelope signal shows similar behaviour up to 5 kHz whereas above the 5 kHz frequency the trend becomes different for normal and faulty signals. For instance, normal signal has a harmonic at 6 kHz frequency. However, faulty signal does not have such harmonic structure. For multiple hits (2nd column in Fig. 5) in turn, we can observe the harmonic structure of the signals at different frequencies. Although the envelope spectra of both normal and faulty signals mostly show similar trends, they differ in 6-7 kHz frequency range. The normal signal has a single harmonic within this range, the faulty signal has 2 harmonics in the same range.



**Figure 4.** Long-Term average spectra for single (left) and multiple hits (right) vibration data.

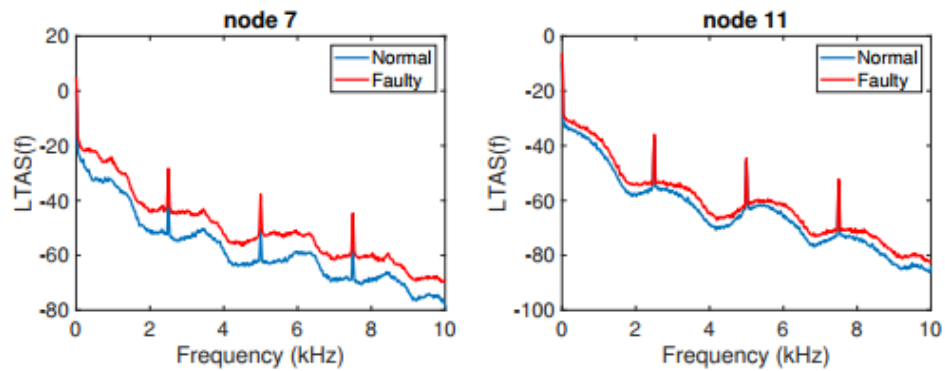


**Figure 5.** Long-Term average spectra computed from envelope signals for single (left) and multiple hits (right) vibration data.

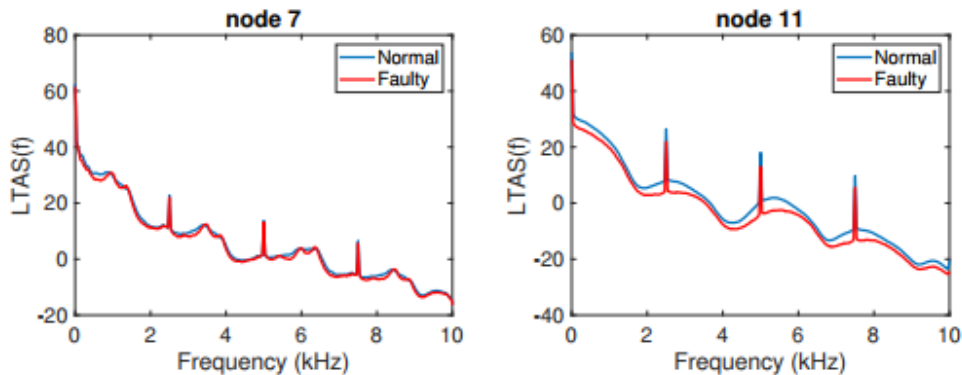
### 3.3.2. WPT Analysis

The last fault diagnosis experiments are carried out using the signals obtained from the different nodes of the WPT. To this end we first construct a wavelet packet tree consisting of three levels as described in section 2.3 and then processed original signals through tree and the signals reconstructed at the different nodes of the tree are used for fault diagnosis analysis. The envelope of the reconstructed signals at different nodes are computed and then LTAS of the envelope signals are calculated. Experimentally we analyzed each node of the tree and found that the nodes 7 and 11 give the most interesting results. Therefore we report the analyses using signals obtained from these nodes.

Fig. 6 and Fig. 7 show the LTAS of the envelope of the reconstructed signals from nodes 7 and 11 for single and multi- hits, respectively. Interestingly, we can see that the envelope spectra contain three impulses and they are located exactly at the same frequency for normal and faulty signals. This observation holds true for both node 7 and node 11. The energy of the normal and faulty signals obtained from the 7th node of the WPT are different for different frequency locations. However, the energy of the signals are very similar for the signal corresponding to 11th node of the WPT.



**Figure 6 .** Envelope spectra computed from the signals reconstructed from the nodes 7 and 11 of WPT for single vibration data.



**Figure 7 .** Envelope spectra computed from the signals reconstructed from the nodes 7 and 11 of WPT for multiple hits vibration data.

For the multiple hits case (case 2), in contrast to single hit case (Fig. 6), the envelope spectra of the normal and faulty signals obtained from the 7th node of the WPT have very similar trends and both signals have the similar energy distributions over the frequency. However, except from the three impulses, there exist other harmonics in the spectra and faulty signal have more harmonic components than the normal signal. The number of these harmonics reduces in the case of 11th node signal and these harmonics are disappears. There are only three impulses in the envelope spectra of the 11th node signals.

#### 4. Conclusions

In this paper, we addressed the problem of fault diagnosis using the vibration signals collected from the mechanical transfer press. We analysed the signals using four different analysis methods. Experiments were conducted on normal and faulty signals consisting of single hits (case 1) and multiple hits (case 2). We found that normal and faulty signals considerably differ at low (below 2 kHz) and high (above 8 kHz) frequency regions when both signals contains only a single hit. In case of both signals consist of multiple successive press hits (case 2), the differences in low frequency region was found to be diminished and a spectral peak/impulse at 5 kHz for both normal and faulty signals occurred. When signals were analysed using wavelet packet transform, we observed three impulses for each signal (normal and faulty) occurring exactly at the same frequency values.

#### 5. Acknowledgements

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