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Analysis of Fault Signal in Gear Using Higher Order Time Frequency Analysis

고차 시간- 주파수 해석에 의한 기어의 고장 신호 해석

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ABSTRACT

Impulsive acoustic and vibration signals within gear are often induced by impacting of fault tooths in gear. Thus the detection of these impulses can be useful for fault diagnosis. Recently there is an increasing trend towards the use of higher order statistics for fault detection within mechanical systems based on the observation that impulsive signals tend to increase the kurtosis values. We show that the fourth order Wigner Moment Spectrum, called the Wigner Trispectrum, has found superior detection performance to second order Wigner distribution for typical impulsive signals in a condition monitoring application. These methods are also applied to data sets measured within an industrial gear box.

Key words : Gear, Impulsive Sound, Higher Order Time Frequency Analysis

1 Introduction

Recently interest in the use of time-frequency methods for fault diagnosis in rotating machinery based on acoustic or vibration data[1] has grown. Such methods allow one to describe simultaneously when a fault occurs and its frequency content. The bilinear class of distributions have the advantage that they can be constrained to yield real distributions which can interpreted as two dimensional decompositions of a signals energy. The Wigner-Ville distribution (WVD), which is one of the class of bilinear distributions, has been widely acknowledged as a convenient signal processing tool because of its various attractive properties[2], the most important of which is the Wigner-Villes good resolution capabilities. However, it also possesses the unwanted property of containing interference terms when the input signal contains several components. In order to mitigate this problem the Choi-Williams distribution[3] was developed.

Acoustic and vibration data from gear have

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been used for fault detection for a long time. These data usually consist of tonal signals, periodic impulses due to the fault and broadband noise. The impulsive components are often hidden by the competing signal components. Recently a pre-processor, dubbed the two-stage ALE (Adaptive Line Enhancer)(4), has been proposed for enhancing the impulsive signals prior to analysis with a bilinear time-frequency method. However, at low Signal to Noise Ratios (SNRs) significant residual noise can remain even after enhancement. This residual noise is generally dominated by the broadband components, which can serve to cause significant problems in the bilinear time-frequency analysis. We seek to explore the use of alternative time-frequency tools for this last analysis stage. Specifically we seek methods which are inherently more robust in the presence of random (Gaussian) noise. Higher Order Spectral (HOS) analysis has been considered for the detection of impulsive signals in Gaussian noise(5). Time-frequency distributions using HOS have been developed and applied to the detection of FM signals and impulsive signals(6). These methods are based on the higher order extensions to the WVD. In this paper WHOMS (Wigner Higher Order Moment Spectra) are discussed in detail, with emphasis on the cross-terms and ambiguity function. Finally it is shown that useful quantitative information can be extracted from this analysis about the timing of the impulses and their spectral characteristics.

2. Higher Order Wigner-Ville Moment Distribution

For a long time power spectra (and autocorrelation functions) have played an important role in extracting information from time series. Power spectra describe the second order statistics of a stationary process. The bilinear class of time-frequency representations describe a signals second order statistics as a function of time, so are suited to the analysis of nonstationary signals. Recent research has studied time varying HOS for analyzing nonstationary signals. Gerr(7) proposed a definition for the 3rd order WVD for deterministic signals. This definition was later extended to a general order WVD termed the Wigner Higher Order Moments Spectra(8) (WHOMS). These exploit the instantaneous n+1th order moment function. Hence for a stationary random process the expected value of WHOMS reduces to the higher order moment spectra. The WHOMS preserve and generalize all the important properties of WVD.

2.1 Definition of Wigner Higher Order Moment Spectra (WHOMS)

Wigner Higher Order Moment Spectra of order n+1th is defined by Fonosolla(8) as following equation (1):

$$W_{n+1}(\tau, f_1, .., f_n) = \int_{\tau_1} .. \int_{\tau_n} R^i_{n+1}(t, \tau_1, .., \tau_n) \prod_{i=1}^{n} e^{-2j\pi f_i \tau_i} d\tau_i \quad (1)$$

where

$$R^i_{n+1}(t, \tau_1, ..., \tau_n) = s^*(t-\alpha) \prod_{i=1}^{n} s(t+\tau_i-\alpha) \quad (2)$$

In order to extend most of the properties of the WVD, the lag centring condition has to be imposed, leading to

$$\alpha = \frac{1}{n+1} \sum_{i=1}^{n} \tau_i \quad (3)$$

and thus WHOMS is rewritten as

$$W_{n+1}(t, f_1, .., f_n) = \int_{\tau_1} .. \int_{\tau_n} s^*(t - \frac{1}{n+1} \sum_{m=1}^{n} \tau_m) \prod_{i=1}^{n} s(t + \frac{n}{n+1}\tau_i - \frac{1}{n+1} \sum_{k=1, k\neq i}^{n} \tau_k) e^{-2\pi j f_i \tau_i} d\tau_i \quad (4)$$

Therefore we can obtain the Wigner

Bispectrum (WB) and the Wigner Trispectrum (WT) using equation (4) as follows;

(a) WVD (n=1)

$$W_2(t,f) = \int_{\tau} s^*(t-\tau/2)s(t+\tau/2)e^{-2\pi jf\tau}d\tau \qquad (5)$$

(b)WB(n=2)

$$W_3(t,f_1,f_2) = \iint s^*(t-\frac{\tau_1+\tau_2}{3})s(t+\frac{2\tau_1-\tau_2}{3}) s(t+\frac{2\tau_2-\tau_1}{3})e^{-2\pi j(f_1\tau_1+f_2\tau_2)}d\tau_1 d\tau_2 \qquad (6)$$

(c) Symmetric WT (n=3)

$$W_4(t,f_1,f_2,f_3) = \iiint s^*(t-\tau)s(t-\tau+\tau_1)s(t-\tau+\tau_2) s(t-\tau+\tau_3)e^{-2\pi j(f_1\tau_1+f_2\tau_2+f_3\tau_3)}d\tau_1 d\tau_2 d\tau_3 \qquad (7)$$

where

$$\tau = \frac{\tau_1+\tau_2+\tau_3}{4} \qquad (8)$$

2.2 WHOMS for Multi-Component Signals

Whilst the WVD has significant resolution advantages over other time-frequency methods, its application is dogged by problems associated with cross/interference terms. If we consider a signal x(t) which consists of two components $x_1(t)$ and $x_2(t)$, such that :

$$x(t) = x_1(t) + x_2(t) \qquad (9)$$

Consider a specific form of the two components,

$$x_1(t) = s(t-t_1)e^{-2\pi j\omega_1 t} \qquad (10.a)$$

$$x_2(t) = s(t-t_2)e^{-2\pi j\omega_2 t} \qquad (10.b)$$

where s(t) is a prototype signal, t_1 and t_2 are time shifts and 1 and 2 are frequency shifts. In general, the n+1th order Wigner distribution for a two component signal is the sum of 2n+1 distributions, of which two are auto terms whilst 2n+1-2 are cross terms. In the following we detail all these terms for the WVD, WB and WT for a signal of the form described by (9) and (10).

Auto-terms and cross-terms for the WVD.

a) auto-terms

$$W_{11}(t,\Omega) = W_{ss}(t-t_1,\Omega-\omega_1)$$
$$W_{22}(t,\Omega) = W_{ss}(t-t_2,\Omega-\omega_2) \qquad (11)$$

b) cross-terms(9)

$$W_{12}(t,\Omega) = W_{ss}(t-t_m,\Omega-\omega_m)e^{-j(\Omega t_d-\omega_d t-\omega_d t_d)}$$
$$(W_{21}(t,\Omega) = W_{ss}(t-t_m,\Omega-\omega_m)e^{j(\Omega t_d-\omega_d t-\omega_d t_d)} \qquad (12)$$

where $\omega_1=2\pi\alpha$, $\omega_2=2\pi\beta$, $\Omega=2\pi f$, $t_m=(t_1+t_2)/2$, $\omega_m=(\omega_1+\omega_2)/2$ and $t_d=t_1-t_2$. $W_{ss}(t,\Omega)$ is WVD of s(t)

Auto-terms and cross-terms for WB

a)auto-terms

$$W_{111}(t,\Omega_1,\Omega_2) = W_{sss}(t-t_1,\Omega_1-\frac{2}{3}\omega_1,\Omega_2-\frac{2}{3}\omega_2)e^{-j\omega_1 t}$$
$$W_{222}(t,\Omega_1,\Omega_2) = W_{sss}(t-t_2,\Omega_1-\frac{2}{3}\omega_1,\Omega_2-\frac{2}{3}\omega_2)e^{-j\omega_2 t} \qquad (13)$$

b) cross-terms

$$W_{112}(t,\Omega_1,\Omega_2) = W_{sss}(t-t_{m_1},\Omega_1-\omega_{d1},\Omega_2-\frac{2}{3}\omega_2)\cdot e^{j(\Omega_2 t_d+\omega_2 t-2\omega_2 t_d/3)}$$

$$W_{121}(t,\Omega_1,\Omega_2) = W_{sss}(t-t_{m_1},\Omega_1-\frac{2}{3}\omega_2,\Omega_2-\omega_{d1})\cdot e^{j(\Omega_1 t_d+\omega_2 t-2\omega_2 t_d/3)}$$

$$W_{211}(t,\Omega_1,\Omega_2) = W_{sss}(t-t_{m_1},\Omega_1-\omega_m,\Omega_2-\omega_m)\cdot e^{-j(\Omega_1+\Omega_2)t_d-j(\omega_2-2\omega_1)t+j2\omega_m t_d}$$

$$W_{122}(t,\Omega_1,\Omega_2) = W_{sss}(t-t_{m_2},\Omega_1-\omega_m,\Omega_2-\omega_m)\cdot e^{j(\Omega_1+\Omega_2)t_d-j(\omega_1-2\omega_2)t+j2\omega_m t_d}$$

$$W_{221}(t,\Omega_1,\Omega_2) = W_{sss}(t-t_{m_2},\Omega_1-\omega_{d2},\Omega_2-\frac{2}{3}\omega_1)\cdot e^{-j(\Omega_2 t_d-\omega_1 t-2\omega_1 t_d/3)} \qquad (14)$$

$$W_{212}(t,\Omega_1,\Omega_2) = W_{sss}(t-t_{m_2},\Omega_1-\frac{2}{3}\omega_1,\Omega_2-\omega_{d2})\cdot e^{-j(\Omega_1 t_d-\omega_2 t-2\omega_2 t_d/3)}$$

where t_{m_1} t_{m_2} = (t1+2t2) /3, t_m = $(t_1+t_2)/2$, $t_d=t_1-t_2$, Ω_1= $2f_1$, Ω_2= $2f_2$, $\omega_1=2\pi\alpha$, $\omega_2=2\pi\beta$,

$\omega_{d1} = \omega_1 - \omega_2/3$, $\omega_{d2} = \omega_2 - \omega_1/3$, $\omega_m = (\omega_1 + \omega_2)/3$ and $W_{sss}(t, \Omega_1, \Omega_2)$ is the WB for a signal $s(t).= (2t_1+t_2)/3$,

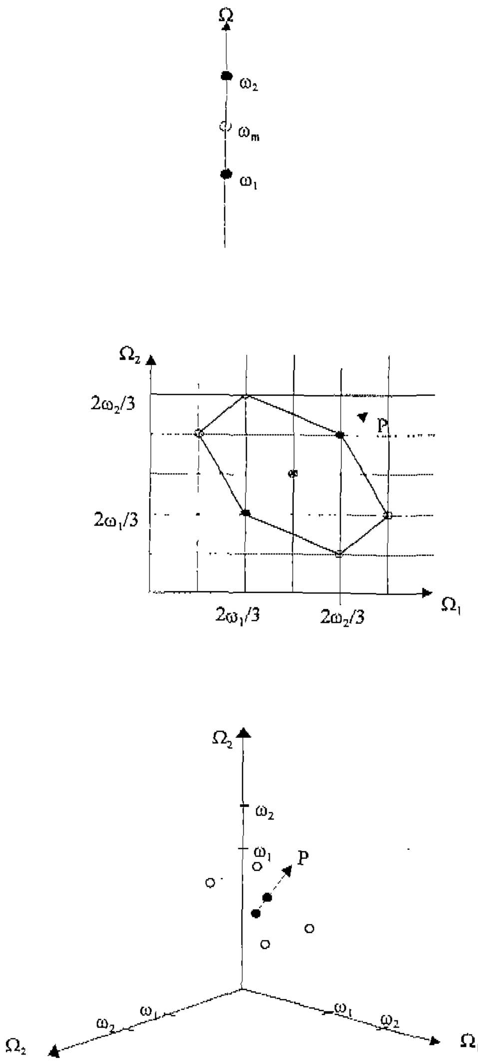


Fig.1 Pictorial explanation for the WHOMS (a) WVD at time t0 (b) WB at time t0 (c) WT at time t0 : P designates the principal slice. circles are the cross-terms and black circles are auto-terms.

Auto-terms and cross-terms for WT

a)auto-terms

$$W_{1111} = W_{ssss}(t - t_1, \Omega_1 - \omega_1, \Omega_2 - \omega_1, \Omega_3 + \omega_1)$$
$$W_{2222} = W_{ssss}(t - t_2, \Omega_1 - \omega_2, \Omega_2 - \omega_2, \Omega_3 + \omega_2) \quad (15)$$

b)cross-terms

$$W_{1112} = W_{ssss}(t - t_{m_1}, \Omega_1 - \omega_{m1}, \Omega_2 - \omega_{m1}, \Omega_3 + \omega_{m2}) \cdot e^{j(\Omega_3 t_d + \omega_d t + \omega_{m2} t_d)}$$

$$W_{1121} = W_{ssss}(t - t_{m_1}, \Omega_1 - \omega_{d1}, \Omega_2 - \omega_{m1}, \Omega_3 + \omega_{m2}) \cdot e^{j(\Omega_2 t_d - \omega_d t - \omega_{m2} t_d)}$$

$$W_{1211} = W_{ssss}(t - t_{m_1}, \Omega_1 - \omega_{m2}, \Omega_2 - \omega_{d1}, \Omega_3 + \omega_{m1}) \cdot e^{j(\Omega_1 t_d - \omega_d t + 3\omega_{m2} t_d)}$$

$$W_{2111} = W_{ssss}(t - t_{m_1}, \Omega_1 - \omega_{m1}, \Omega_2 - \omega_{m1}, \Omega_3 + \omega_{d1}) \cdot e^{-j((\Omega_1 + \Omega_2 + \Omega_3) t_d - \omega_d t - \omega_{m2} t_d)}$$

$$W_{1222} = W_{ssss}(t - t_{m_2}, \Omega_1 - \omega_{m2}, \Omega_2 - \omega_{m2}, \Omega_3 + \omega_{d2}) \cdot e^{j((\Omega_1 + \Omega_2 + \Omega_3) t_d - \omega_d t - \omega_{m1} t_d)}$$

$$W_{2221} = W_{ssss}(t - t_{m_2}, \Omega_1 - \omega_{m2}, \Omega_2 - \omega_{m2}, \Omega_3 + \omega_{m1}) \cdot e^{-j(\Omega_3 t_d + \omega_d t + \omega_{m1} t_d)}$$

$$W_{2212} = W_{ssss}(t - t_{m_2}, \Omega_1 - \omega_{d2}, \Omega_2 - \omega_{m1}, \Omega_3 + \omega_{m2}) \cdot e^{-j(\Omega_2 t_d - \omega_d t - \omega_{m1} t_d)}$$

$$W_{2122} = W_{ssss}(t - t_{m_2}, \Omega_1 - \omega_{m1}, \Omega_2 - \omega_{d2}, \Omega_3 + \omega_{m2}) \cdot e^{-j(\Omega_1 t_d - \omega_d t - \omega_{m1} t_d)}$$

$$W_{1122} = W_{ssss}(t - t_m, \Omega_1 - \omega_1, \Omega_2 - \omega_2, \Omega_3 + \omega_2) \cdot e^{j(\Omega_2 + \Omega_3) t_d}$$

$$W_{2211} = W_{ssss}(t - t_m, \Omega_1 - \omega_2, \Omega_2 - \omega_1, \Omega_3 + \omega_1) \cdot e^{-j(\Omega_2 + \Omega_3) t_d}$$

$$W_{1212} = W_{ssss}(t - t_m, \Omega_1 - \omega_2, \Omega_2 - \omega_1, \Omega_3 + \omega_2) \cdot e^{j(\Omega_1 + \Omega_3) t_d}$$

$$W_{2121} = W_{ssss}(t - t_m, \Omega_1 - \omega_2, \Omega_2 - \omega_1, \Omega_3 + \omega_2) \cdot e^{-j(\Omega_1 + \Omega_3) t_d}$$

$$W_{2112} = W_{ssss}(t - t_m, \Omega_1 - \omega_m, \Omega_2 - \omega_m, \Omega_3 + \omega_m) \cdot e^{j((\Omega_1 + \Omega_2) t_d - 2\omega_d t + 2\omega_m t_d)}$$

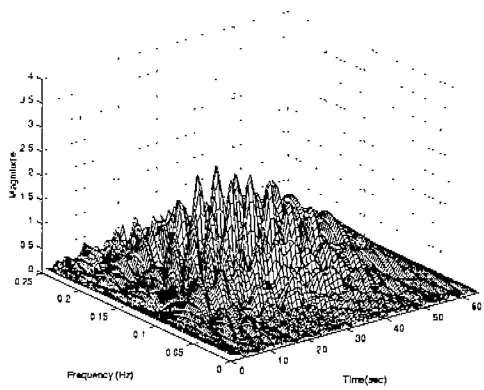
$$W_{1221} = W_{ssss}(t - t_m, \Omega_1 - \omega_m, \Omega_2 - \omega_m, \Omega_3 + \omega_m) \cdot e^{-j((\Omega_1 + \Omega_2) t_d - 2\omega_d t - 2\omega_m t_d)} \quad (16)$$

where $t_{m_1} = t_{m_2} = (t_1+3t_2)/4$, $t_m = (t_1+t_2)/2$, $t_d = t_1-t_2$, $\omega_d = \omega_1 - \omega_2$, $\Omega_1 = 2f_1$, $\Omega_2 = 2f_2$, $\Omega_3 = 2f3$, $\omega_1 = 2\pi\alpha$, $\omega_2 = 2\pi\beta$, $\omega_{d1} = (5\omega_1 - \omega_2)/4$, $\omega_{d2} = (5\omega_2 - \omega_1)/4$, $\omega_{m1} = (3\omega_1 + \omega_2)/4$, $\omega_{m2} = (\omega_1 + 3\omega_2)/4$, $\omega_m = (\omega_1 + \omega_2)/2$ and Wssss(t, Ω_1, Ω_2, Ω_3) is the WT for a signal s(t).

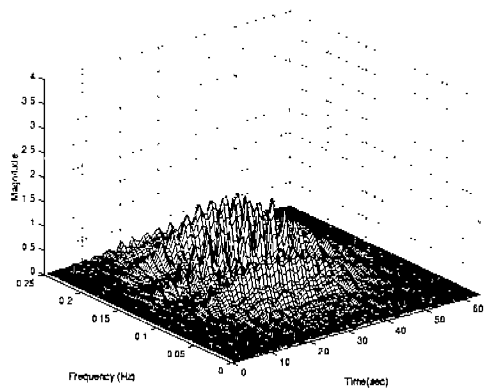
2.3 Slice Wigner higher Order Moment Spectra

The full WHOMS is a function of n+1 variables, time and n frequency variables. This presents problems when attempting to display results, since the resulting plots exist in n+2 dimensional space. Further, there is also a heavy computational burden as one is required to perform n dimensional FFTs for each time segment. For these reasons it is common to consider a subset of the WHOMS called the principal slice. The principal slice consists of the plane defined by $\Omega 1 = \Omega 2 = ... = \Omega$; all values of t are considered. This slice includes both auto-terms and cross-terms, however the number of cross-terms is significantly reduced.

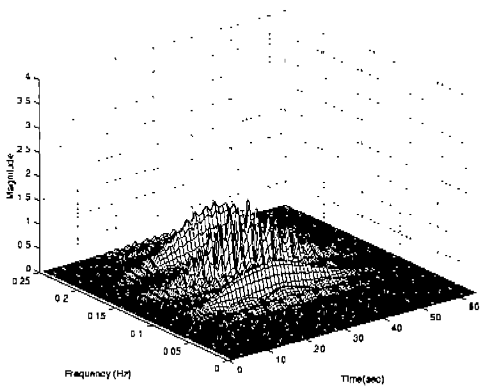
Figure 1 shows a pictorial explanation of the principal slice for the WHOMS using a signal x(t) which consists lincar sum of $x_1(t) = A_0\exp(j\omega_1(t))$ and $x_2(t) = A_0\exp(j\omega_2(t))$. In this figure the black circles are auto-terms and the circles represent the cross-terms, the "P" denotes the principal slice. Figure 1(a) shows the WVD for a signal x(t) at arbitrary time t0. According to (12) the cross-terms arc real and oscillate along the time axis. Figure 1(b) shows the WB for a signal x(t) at arbitrary time t0 there are 6 cross-terms. However, if we use the principal slice, these are reduced to only two cross-terms. But these two cross terms are complex, see (14). In particular even auto-terms in the WB are complex in nature; consequently it is common to consider only the magnitude of the WB. The SWB (Sliced WB) is obtained by setting $\Omega_1 = \Omega_2 = ... = \Omega$ in the definition of the WB.



(a)



(b)



(c)

Fig.2 Comparison of the effect of Gaussian noise added to signal x(t) (a) WVD (b) SWB (c) SWT

Figure 1(c) shows the WT for x(t) at arbitrary time t0. Similarly to the SWB the SWT (Slice WT) is obtained by setting $\Omega_1 = \Omega_2 = -\Omega_3 ..... = \Omega$ in the definition of the WT. From (16) we see there are 14 cross-terms in the WT but, in this example (assuming $\omega_1 \neq \omega_2$), if we use the SWT these reduce to only two. These two cross terms in the SWT are real and oscillate between the two auto-terms. The auto-terms in the WVD and the SWT are sinusoidal with amplitudes A_0^1 and A_0^2 respectively. If Gaussian random noise n(t) with SNR (σ_0^2/A_0^2) <1 is added to x(t) where σ_0^2 is noise variance, then the relative magnitudes ($A_0^4(1-\sigma_0^4/A_0^4)$) of the SWT for signal x(t) to that for noise n(t) are larger and clearer than the relative magnitudes ($A_0^2(1-\sigma_0^2/A_0^2)$ of the WVD. Figure 2 illustrates this result. Figures 2(a),(b) and (c) show the WVD, SWB and SWT respectively, for x(t) with added Gaussian noise (σ_0^2=0.5). The signal x(t) contains two sine waves with center frequencies 0.1Hz and 0.2Hz. The amplitude (A_0) of each sine wave is one. Therefore it is identified that the SWB and SWT for deterministic signals are less sensitive to Gaussian random noise than the WVD. However both the SWB and the SWT for the signal x(t) still suffer from cross terms. The reduction of these cross terms via smoothing will be discussed in the next section.

3. Ambiguity Function

The ambiguity function has been widely used in the context of radar and sonar, its definition is [10]

$$A(\xi,\tau) = \int s(t+\frac{\tau}{2})s^*(t-\frac{\tau}{2})e^{-2\pi j\xi t}\,dt \qquad (17)$$

where $R(t,\tau)=s(t+\tau/2)s^*(t-\tau/2)$ is the instantaneous auto-correlation of s(t), τ is frequency lag and ξ is frequency lag. The ambiguity function can also be regarded as a decomposition of a signals energy, since when it is integrated over the (ξ, τ) plane one obtains the signals energy. The ambiguity function and the WVD are related via a double Fourier transform pair.

As discussed in the previous section the WVD is a convenient tool for the time-frequency analysis of mono-component non-stationary signals. However, in the case of multi-component signals, its bilinear structure also leads to the generation of unwanted cross-terms, which lack any physical significance. Flandrin[11] introduced a method for separating cross- and auto-terms based on the ambiguity function. The method relies on the fact that auto-terms appear in the ambiguity plane along loci passing through the origin, whilst the loci of cross-terms do not pass through the origin. This observation leads to the definition of a generalized ambiguity function[12]:

$$A_g(\xi,\tau) = \Phi(\xi,\tau)A(\xi,\tau) \qquad (18)$$

in which $\Phi(\xi,t)$ is a weighting function which emphasizes auto-terms at the expense of the cross-terms. To achieve this (ξ,t) is designed to have a low-pass structure in the (ξ,t) plane. Using this principle, many different bilinear time-frequency analysis methods have been developed, such as, the Choi-Williams distribution[3] and the cone kernel distribution[13], along with methods which adaptively select the kernel function[14]. The double inverse Fourier transform of the generalized ambiguity function yields the generalized time-frequency distribution. Here we shall consider the kernel function introduced by Choi and Williams because it is effective for impulsive signals [15]:

$$\Phi(\xi,\tau) = e^{-\xi^2\tau^2/\sigma} \qquad (19)$$

where (σ>0) is a scaling factor and controls the kernel shape. Similarly higher order ambiguity functions can be defined as (multi-dimensional) inverse Fourier transforms of the WHOMS and their sliced versions. For the previous example, (10), the sliced ambiguity function equivalents of (11)-(16) and (17) are given in (20)-(22).

① Ambiguity function for the WVD

$$
\begin{aligned}
A_{11}(\xi,\tau) &= A_{ss}(\xi,\tau)e^{-j(\xi_1-\omega_1\tau)} \\
A_{22}(\xi,\tau) &= A_{ss}(\xi,\tau)e^{-j(\xi_2-\omega_2\tau)} \\
A_{12}(\xi,\tau) &= A_{ss}(\xi-\omega_d t,\tau)e^{j\omega_m\tau} \\
A_{21}(\xi,\tau) &= A_{ss}(\xi+\omega_d t,\tau)e^{j\omega_m\tau}
\end{aligned} \tag{20}
$$

where Ass(ξ , τ) is the ambiguity function of s(t).

Ambiguity functions for the SWB

$$
\begin{aligned}
A_{111}(\xi,\tau) &= A_{sss}(\xi+\omega_1,\tau)e^{-j\omega_1\tau/3} \\
A_{222}(\xi,\tau) &= A_{sss}(\xi+\omega_2,\tau)e^{-j\omega_2\tau/3} \\
A_{112}(\xi,\tau) &= A_{sss}(\xi+(\omega_2-2\omega_1),\tau)e^{j\omega_m\tau} \\
A_{221}(\xi,\tau) &= A_{sss}(\xi+(\omega_1-2\omega_2),\tau)e^{j\omega_m\tau}
\end{aligned} \tag{21}
$$

where Asss(,) is the 3rd order sliced ambiguity function of s(t).

②Ambiguity function for the SWT

$$
\begin{aligned}
A_{1111}(\xi,\tau) &= A_{ssss}(\xi,\tau)e^{j\omega_1\tau} \\
A_{2222}(\xi,\tau) &= A_{ssss}(\xi,\tau)e^{j\omega_2\tau} \\
A_{1221}(\xi,\tau) &= A_{ssss}(\xi+2\omega_d t,\tau)e^{j\omega_m\tau} \\
A_{2112}(\xi,\tau) &= A_{ssss}(\xi-2\omega_d t,\tau)e^{j\omega_m\tau}
\end{aligned} \tag{22}
$$

where Assss(ξ , τ) is the 4th order sliced ambiguity function of s(t). By examining (20) and (22) we see that for the WVD and SWT the auto-terms are all concentrated about the origin, but the cross-terms are concentrated about ($\xi \pm 2\omega_d, \tau$). Thus a suitably chosen kernel function can suppress cross-terms. However, from (21) we see the SWBs ambiguity function has auto-terms which are not concentrated at origin. This makes it difficult to design a kernel to reduce cross-terms in the SWB.

4. Application of WHOMS to Fault Detection in Gear

The impulsive signals generated by faults in a rotating machine are generally immersed in a variety of harmonic and broadband signals(18,19). If such raw signals are analysed using the WVD (or SWT) the plethora of cross-terms created makes interpretation of the time-frequency plot extremely difficult. To overcome this problem we pre-process our signals, prior to the time-frequency analysis, to reduce tonal signals and to eliminate some of the broadband noise using methods described in reference [4,16], referred to as the two-stage ALE (Adaptive Line Enhancer). In this section we compare the use of the WVD and SWT for use in the time-frequency analysis of the pre-processed signals. The problem of fault detection in industrial gears has received wide attention(1,17). Figure 3(a) shows a vibration signal measured from faulty gear and its Fourier transform in Figure 3(b).

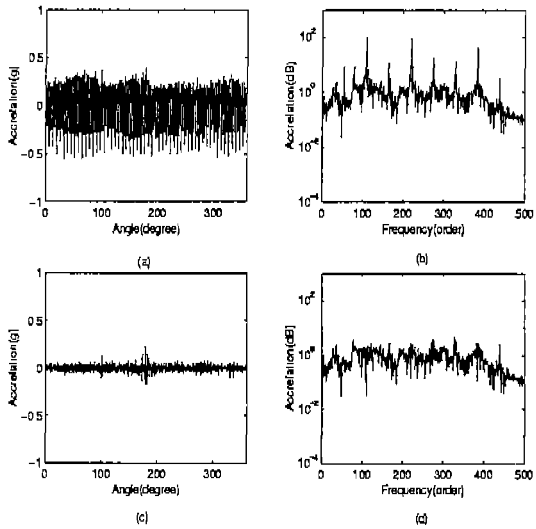
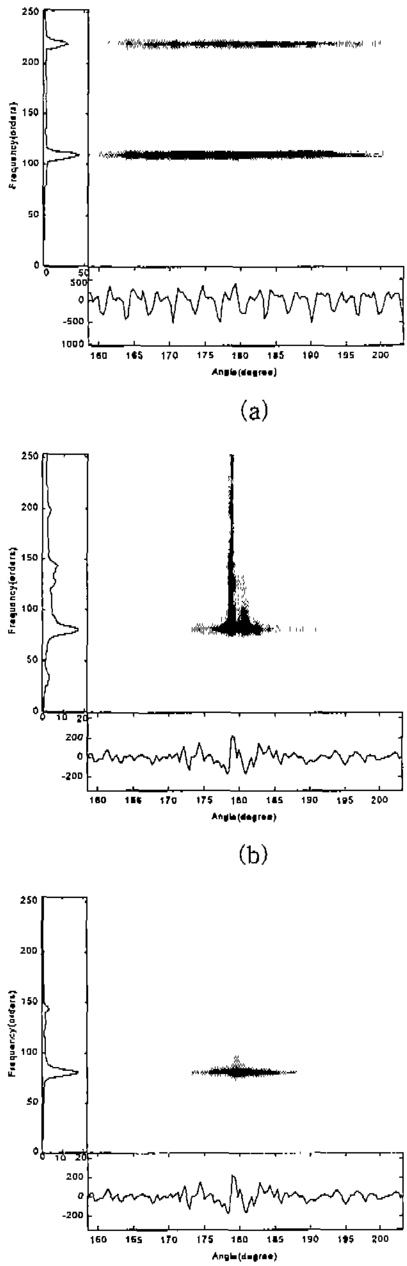


Fig.3 Using two-stage ALE the detection of impulsive sound due to fault of industrial gear; (a) Vibration signal measured on the industrial gear box. It shows the meshing frequency and its harmonic components (b) FFT of raw signal (c) Impulsive signal after pre-processing using two-stage ALE. (d) FFT of processed signal

In order to remove the regular signal, *i.e.* the periodic signals at the fundamental and harmonics of the tooth meshing frequency, the two-stage ALE is again applied, the resulting (residual) signal is shown in Figure 3(c) and its Fourier transform in Figure 3(d). Figure 4(a) shows the CWD(Choi-Williams Distribution) of the raw signal. Again the masking effects of the gear meshing frequencies serve to hide the impulsive signal. However, the CWD of the pre-processed signal, Figure 4(b), reveals some information about the signal structure but is still unsatisfactory for identifying the frequency (order) information of fault signal. If we apply the SWT to the residual signal one obtains the result shown in Figure 4(c). This result is obtained by smoothing with an exponential kernel. From these results, we surmise that that the gear fault occurs at a shaft angle of 180° and is centred a frequency corresponding to the 82 order of shaft rotating speed. From these results it appears that the SWT may offer a more effective for identifying the frequency (order) information for fault signal in fault gear.

5. Conclusions

This paper has demonstrated that the WHOMS (Wigner Higher-Order Moment Spectra) have potentially significant advantages over the WVD (Wigner Ville Distribution) in a condition monitoring environment. In order to exploit WHOMS it is necessary to work in some reduced domain, in this case the slice domain proved effective. The SWT (Sliced Wigner Trispectrum) has the advantage over the SWB (Sliced Wigner Bispectrum) of being easier reduce cross-terms by smoothing. It is also a more natural tool since the SWT utilised fourth order moments of a signal, which have previously been considered for condition monitoring.



(a)

(b)

(c)

Fig.4 Time frequency analysis for measured data on the gear box with fault toots (a) the CWD for raw signal (b) CWD for pre-processed signal by two-stageALE (c) SWT with exponential kernel for pre-processed signal by two-stageALE

It has been demonstrated that visually the results from the SWT are more pleasing than those of the WVD. Moreover rigorous analysis, based on ROC (Receive Operating Characteristic) curves, has demonstrated[20] that its performance is better than WVD for detection purposes.

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