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Adaptive Noise Cancelling and Time-frequency Techniques for Rail Surface Defect Detection

B. Liang^{*1} S. Iwnicki¹, A. Ball¹ and S. Zhang²

¹*School of Computing and Engineering
University of Huddersfield, Huddersfield HD1 3DH, UK*

²*Beijing Institute of Space Launch Technology
P.O. Box 9200-71 Beijing 100076, China*

**Correspondence author b.liang@hud.ac.uk*

Abstract

Adaptive noise cancelling (ANC) is a technique which is very effective to remove additive noises from the contaminated signals. It has been widely used in the fields of telecommunication, radar and sonar signal processing. However it was seldom used for the surveillance and diagnosis of mechanical systems before late of 1990s. As a promising technique it has gradually been exploited for the purpose of condition monitoring and fault diagnosis. Time-frequency analysis is another useful tool for condition monitoring and fault diagnosis purpose as time-frequency analysis can keep both time and frequency information simultaneously. This paper presents an ANC and time-frequency application for railway wheel flat and rail surface defect detection. The experimental results from a scaled roller test rig show that this approach can significantly reduce unwanted interferences and extract the weak signals from strong background noises. The combination of ANC and time-frequency analysis may provide us one of useful tools for condition monitoring and fault diagnosis of railway vehicles.

Key words: *adaptive noise cancelling, wheel-rail contact, time-frequency analysis, signal processing*

1. Introduction

The interest in the ability to monitor system structure integrity and detect damage at the earliest possible stage is persistent throughout the civil, mechanical and aerospace engineering communities. Due to the fact that many such systems are complex, dynamic and time-varying, the necessary signal pre-processing and analysis techniques are required in order to extract useful information from raw signals. The signal pre-processing methods are to condition the raw signals and make every effort to eliminate the unwanted noise from the raw signals while signal analysis techniques are to extract signal features from the conditioned raw signals. One of the well-known techniques in communication area for raw signal pre-processing is adaptive noise cancellation (ANC). ANC is a technique which is very useful to remove additive noises from the contaminated raw signals. It was firstly reported in 1975 that ANC was successfully applied to subtract a pregnant woman's heart rate interference from the very weak foetus heart rate monitoring [1]. Then this technique was widely used in telecommunication, radar and sonar signal processing because of its good performance in applications of noise

reduction. The results from experiments of speech enhancement and speech recognition are especially encouraging [2-3]. After the late 1990s, ANC has also found its application in the area of condition monitoring and fault diagnosis [4-6].

The signal analysis techniques for condition monitoring can be classified into time-domain analysis, frequency-domain analysis, and joint time-frequency domain analysis. The time-domain analysis methods are to identify the quantities of a signal related to its time behaviour such as the maximum amplitude, root mean square (rms) value, kurtosis and crest factor of a signal, while the frequency-domain analysis methods are to analyse the contents of a signal related to its frequency behaviour, like power spectrum, cepstrum and higher-order spectrum of a signal.[7-11]. Since machinery operating in non-stationary mode generates a signature which at each instant of time has a distinct frequency, it is desirable to use time-frequency analysis technique to see how frequency changes with time. Time-frequency analysis techniques had found limited use in the past, except for the last two decades, primarily due to their very high computational complexity and the lack of adequate computing resources of the time. However the fast advances of computers in the last 10 years and the outstanding potential of new time-frequency method like wavelet transform has made them recently a very active area of research [12-16].

Rail and wheel faults like rail surface crack, squats, corrugation, and wheel flat can cause large dynamic contact forces at the wheel–rail interface and lead to fast deterioration of the track. Early detection of such defects is very important for timely maintenance. Extensive theoretical and experimental works have been carried out to investigate what is the best way to identify rail and wheel faults. Jun et al [17] suggested a method of estimating irregularities in railway tracks using acceleration data measured from high-speed trains. A mixed filtering approach was proposed for stable displacement estimation and waveband classification of the irregularities in the measured acceleration. Kawasaki and Youcef-Toumi [18] presented a method based on the car-body acceleration for track condition monitoring. But the car-body acceleration is highly dependent on the primary and the secondary suspension, so the effect of the track irregularities is difficult to extract from such data. Marija and Zili et al [19] attempted to determine a quantitative relationship between the characteristics of the accelerations and the track defects, axle box acceleration at a squat. The dynamic contact was simulated through finite element modeling. Belotti et al [20] presented a method of wheel flat detection using a wavelet transform method. In their study, a series of accelerometers were put under the rail bed to detect the impact force caused by a wheel flat and the signals were analysed based on the wavelet property of variable time-frequency resolution.

This paper made an attempt to use ANC technique as signal pre-processing in order to increase the signal-to-noise ratio of a signal and also to use time-frequency analysis techniques for time-varying impact excitation caused by rail and wheel surface defects. The paper is presented as follows. Section 2 introduces the basic concepts for ANC and four time-frequency analysis techniques (Short-Time-Fourier-Transform, Wigner-Ville-Transform, Choi-Williams-Transform and Wavelet Transform). In section 3 the

experimental test rig is described. Experimental results and discussion are shown in section 4. Finally conclusions are given in section 5.

2. ANC and time-frequency analysis theories

2.1. Adaptive noise cancelling technique

The principal of ANC is that it makes use of an auxiliary or reference input derived from one or more sensors located in points in the noise or unwanted signal field where the concerned signal is weak. The input is filtered and subtracted from a primary input containing both signal and noise. Because the filtering and subtraction are controlled by an appropriate adaptive process, noise reduction can be accomplished with little distorting the signal or increasing the output noise level. Figure 1 presents the basic philosophy of ANC. It can be seen that the primary input is a combination of the signal source s and the noise source n . The auxiliary input is the noise source n_I which is correlated with the primary input noise source n and is filtered to produce an estimation of the noise source \hat{n} . The system output \hat{s} is the source estimation which is the signal s plus noise source n , and then minus the estimation of noise source \hat{n} with the adaptive filter. If n and \hat{n} are close enough, a better estimation of signal source \hat{s} can be obtained. However there are some conditions attached for this method. The first condition is that the signal source s is uncorrelated with noise signal n and n_I . The second condition is that in order to produce the best estimation of the signal source the ANC system output e has to be minimized in term of least means square of power as follows [21]:

$$e = \hat{s} = (s + n) - \hat{n} \quad (1)$$

Squaring equation 1 and taking expectations in consideration of the first condition mentioned above produces,

$$E[e^2] = E[\hat{s}^2] = E[s^2] + E[(n - \hat{n})^2] + 2E[s(n - \hat{n})] = E[s^2] + E[(n - \hat{n})^2] \quad (2)$$

If the item $E[(n - \hat{n})^2]$ is minimized in the least square means, the best least square estimate of the signal \hat{s} can be achieved with

$$E[e^2] = E[\hat{s}^2] = E[s^2] \quad (3)$$

The least mean squares (LMS) algorithm is used for adjusting the filter coefficients to minimize the cost function. Compared to recursive least squares (RLS) algorithms, the LMS algorithms do not involve any matrix operations. Therefore, the LMS algorithms require fewer computational resources and memories than the RLS algorithms. The implementation of the LMS algorithms also is less complicated than the RLS algorithms. To minimize the mean square error $E[e^2]$ the gradient of $E[s^2]$ with respect to weights w can be set to zero. That is

$$\nabla_w E[e^2] = 0 \quad (4)$$

which yields the Wiener equation

$$\mathbf{w} = \mathbf{R}^{-1}\mathbf{P} \quad (5)$$

Where $\mathbf{R}=\mathbf{E}[(n_I) \cdot (n_I)^T]$ is the auxiliary inputs correlation matrix and $\mathbf{P}=\mathbf{E}[(s+n) \cdot (n_I)]$ is the cross-correlation column vector between the primary and the auxiliary inputs.

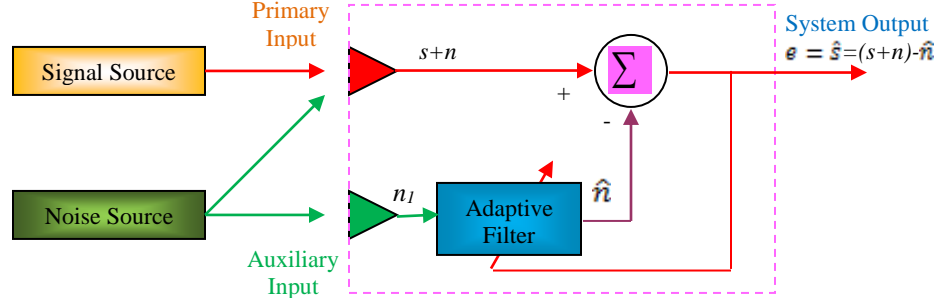


Figure 1 The adaptive noise cancelling concept

2.2. Time-frequency analysis techniques

Time-frequency analysis techniques had found limited use in the past, except for the last two decades, primarily due to their very high computational complexity and the lack of adequate computing resources of the time. However the fast advances of computers in the last 10 years and the outstanding potential of new time-frequency method like wavelet transform has made them recently a very active area of research. The most commonly used time-frequency presentation is the Short-Time-Fourier-Transform (STFT), which was originated from the well-known Fourier transform. In STFT time-localization can be achieved by first windowing the signal so as to cut off only a well-localized slice of $s(t)$ and then taking its Fourier Transform. The STFT of a signal $s(t)$ can be defined as [22]

$$STFT_s(t, \omega) = \int_{-\infty}^{\infty} h(\tau - t) s(t) e^{-j\omega\tau} dt \quad (6)$$

Where τ and ω denote the time of spectral localization and Fourier frequency, respectively, and $h(\tau-t)$ denotes a window function. However the STFT has some problems with dynamic signals due to its limitations of fixed window width.

Another well-known time-frequency representation is the Wigner-Ville transform. The Wigner transform was developed by Eugene Wigner in 1932 to study the problem of statistical equilibrium in quantum mechanics and was first introduced in signal analysis by the French scientist, Ville about 15 years later. It is commonly known in the signal processing community as the Wigner-Ville Transform [23].

Given a signal $s(t)$, its Wigner-Ville transform is defined by

$$WV_s(t, \omega) = \int_{-\infty}^{\infty} s(t + \tau/2) s^*(t - \tau/2) e^{-j\omega\tau} d\tau \quad (7)$$

The Wigner-Ville transform $W_s(t, \omega)$ essentially amounts to considering inner products of copies of $s(t + \tau) e^{-j\omega\tau}$ of the original signal shifted in time-domain with the corresponding reversed copy $s(-t + \tau) e^{j\omega\tau}$. Simple geometrical considerations show that such a procedure provides insights into the time-frequency content of a signal. From the definition of equation (7) it can be seen that the calculation of Wigner-Ville transform requires infinite quantity of the signal, which is impossible in practice. One practical method is to add a window $h(\tau)$ to the signal. That leads to a new version of the Wigner-Ville transform as follows:

$$PWV_s(t, \omega) = \int_{-\infty}^{\infty} h(\tau) s(t + \tau/2) s^*(t - \tau/2) e^{-j\omega\tau} d\tau \quad (8)$$

Which is called pseudo-Wigner-Ville (PWV) representation.

However there is a well-known drawback of using Wigner-Ville distribution. The interference or cross-terms exist between any two signals due to the fact the Wigner-Ville transform is a bilinear transform. For example, if a signal consists of signal 1 and signal 2, the Wigner-Ville transform of the signal is

$$PWV_s(t, \omega) = PWV_{s_1}(t, \omega) + PWV_{s_2}(t, \omega) + 2\mathcal{R}e(PWV_{s_1, s_2}(t, \omega)) \quad (9)$$

Where $PWV_{s_1, s_2}(t, \omega) = \int_{-\infty}^{\infty} h_1(\tau) s_1(t + \tau/2) \cdot h_2(\tau) s_2^*(t - \tau/2) e^{-j\omega\tau} d\tau$ is called the cross term Wigner-Ville transform of signal 1 and signal 2. In order to get rid of the cross-term a smoothed pseudo Wigner-Ville transform (SPWVT) has to be used.

As the Wigner-Ville transform can be generalized to a large class of time-frequency representations called Cohen's class representations, one of natural choices is to select some Cohen's kernel functions which can suppress the cross-term. The Choi-Williams Transform (CWT) is one of them. CWT was first proposed by Hyung-Il Choi and William J. Williams in 1989 [24]. This distribution function adopts exponential kernel to suppress the cross-term. The CWT mathematical definition of a signal s is

$$CW_s(t, \omega) = \iint_{-\infty}^{\infty} \frac{1}{\sqrt{\frac{4\pi\tau^2}{\sigma}}} e^{-\frac{(\mu-t)^2\sigma^2}{4\tau^2}} s(\mu + \tau/2) s^*(\mu - \tau/2) e^{-i\omega\tau} d\mu d\tau \quad (10)$$

The CWT can also be considered as a type of "smoothed WVT" due to the fact that as seen in equation (10) if $\sigma \rightarrow +\infty$, CW will become WVT. On the other hand, the smaller σ is, the better the cross-term reduction is. However, the kernel gain does not decrease along the axes in the ambiguity domain. Consequently, the kernel function of the CWT function can only filter out the cross-terms result from the components differ in both time and frequency centre. Despite this disadvantage, CWT still is one of the most popular time-frequency analysis techniques.

Finally another relatively new time-frequency analysis technique is the wavelet transform (WT). Unlike Fourier analysis which breaks up a signal into sine waves of various frequencies wavelet analysis is to decompose a signal into shifted and scaled versions of the original (or mother) wavelet. One major advantage provided by wavelets is the ability to perform local analysis. Because wavelets are localized in time and scale, wavelet coefficients are able to localize abrupt changes in smooth signals. Also the WT is good at extracting information from both time and frequency domains. However the WT is sensitive to noise.

For a signal $s(t)$, the WT transform can be given as [25]

$$WT_s^\psi(\tau, x) = \Psi_s^\psi(\tau, x) = \frac{1}{\sqrt{|x|}} \int_{-\infty}^{\infty} s(t) \psi^*(t - \tau/x) dt \quad (11)$$

Where $\psi(t-\tau/x)$ is the mother wavelet with a dilation x and a translation τ which is used for localization in frequency and time.

3. The roller test rig and experiments set up

In order to validate the suggested techniques, a series of experiments has been carried out on one 1/5 scale roller rig at University of Huddersfield. A scaled roller rig can offer a number of advantages over a full size roller rig such as a smaller space occupied by the rig and more easily handled. A scaled roller rig can be used to demonstrate the behaviour of a bogie vehicle under various running conditions without losing generality as long as the effect of scaling on the equations of governing the wheel-rail interaction (creep force) is maintained. Our roller rig scaling factor for the mass is 5^3 and the inertia scaling factor is 5^5 which were set according to Kalker's theory. The roller rig consists of four rollers supported in yoke plates incorporating the rollers in supporting bearings. The roller motion is provided by servo hydraulic actuators which are connected directly to the supporting yoke plates, these actuators being controlled by a digital controller which allows the inputs to follow defined waveforms or measured track data. The bogie vehicle parameters were selected to represent those of a typical high speed passenger coach (the BR Mk4 passenger coach). The wheel profile is a machined scale version of the BR P8 profile and the rollers have a scale BS 110 rail profile with no rail inclination.. The parameters for the roller rig are given in Table 1. As indicated in Figure 1 two accelerometers were installed on wheel axle boxes. One dent with a surface size of 3mm long x 2mm wide x 0.2mm deep was made on the surface of one rollers to simulate rail surface defect. One wheel flat with a size of 2mm wide x 1mm long was also made on the wheel paired with the dented roller. The accelerometer with the underneath roller defect was used as the primary input of the ANC filter and another accelerometer without underneath roller defect was linked to the auxiliary input of the ANC filter as indicated in Figure 1-2. The acceleration data were sampled by a YE6231 data acquisition system which has 4 channels, 24-bit resolution and maximum sampling rate 100 kHz.

Table 1 The parameters for the roller rig

Parameter	Full size	1/5 scale
wheelset mass	1850 kg	14.8 kg

wheelset rotational inertia	174 kgm^2	0.056 kgm^2
wheelset roll/yaw inertia	935 kgm^2	0.300 kgm^2
bogie mass	2469 kg	19.75 kg
bogie roll inertia	1130 kgm^2	0.361 kgm^2
bogie yaw inertia	2142 kgm^2	0.685 kgm^2
wheel diameter	0.914 m	0.182 m
gauge	1.435 m	0.287 m
wheelbase	2.5 m	0.5 m
speed	v	$v/5$

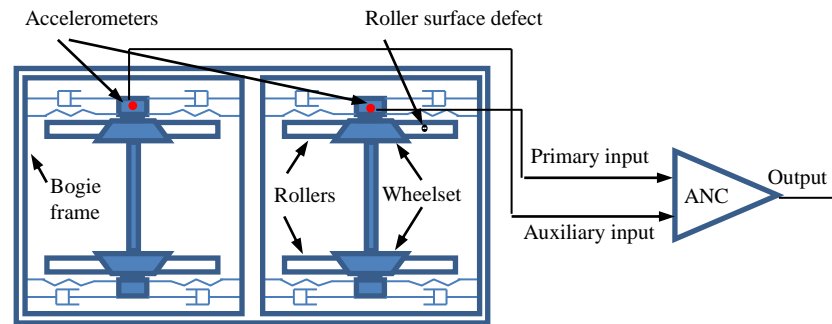


Figure 1 The primary and auxiliary inputs of the ANC filter

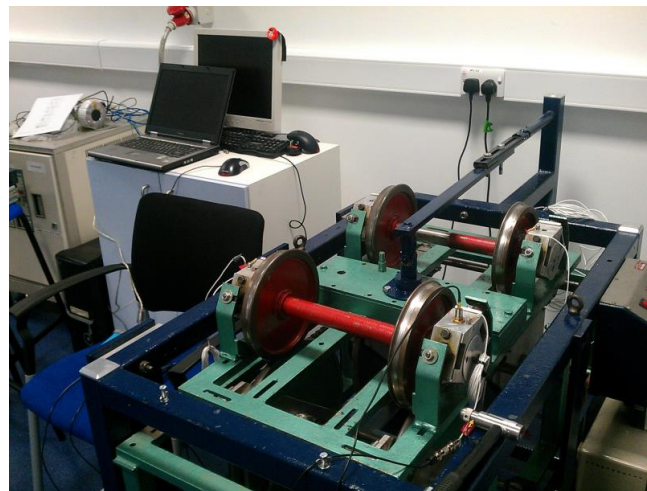


Figure 2 The photo of the 1/5 roller test rig

4. Experimental results and discussions

In figure 3, a series of impact vibration pulses caused by a roller surface defect under three different wheelset running speeds are presented. When the wheelset running speed is low, the clear impact pulses caused by the roller surface defect can be seen (figure 4(a)). However as the wheelset running speed rises, the roller surface defect impact pulses will be contaminated by wheel flange contact and some other unknown noises as shown in figure 4(c). Some kinds of signal processing techniques are necessary in order to eliminate the unwanted noises. Figure 4 presents the corresponding spectra of the impact vibration under different wheelset running speeds. It shows that when wheelset speed is low, the impact caused by the defect can only excite some higher frequency content of the wheelset system (between 2000-2500Hz). As the wheelset speed continues to rise as indicated in figure 4(b)-(c), the higher frequency caused by the impact diminished and the lower band natural frequencies 300-400Hz, 600-650Hz and 1100-1300Hz became the dominant frequencies in the spectrum because the creep forces between wheel and rail were increased with the wheelset rotating speed rising.

Figures 6-8 present some results which show the effects of the ANC noise cancellation for the wheelset running from low to high speeds. Figure 6(a) is the vibration signal of the roller with a surface defect used as the primary input for the ANC filter (the *top* wheel of the right wheelset) and figure 6(b) is the vibration signal of the roller without a surface defect used as auxiliary input for the ANC filter (the *bottom* wheel of the right wheelset), and figure 6(c) is the signal after ANC processing. The slight signal to noise ratio improvement can be seen with and without ANC processing in figure 6. Figure 7 gives the ANC effect for wheelset running speed 15km/h. As expected the impact vibration amplitude is increased proportionally with the wheelset speed and a better ANC cancellation performance is observable in figure 7. When the wheelset running speed continues to rise, the impact signal caused by roller surface defect is severely corrupted by some unwanted noises like the wheelset lateral movement and the contact between wheel flanges and rollers (figure 8(a)). However the ANC processing can still recover the corrupted impact signal well as demonstrated in figure 8(c) despite there is a low signal-to-noise ratio when compared with the low wheelset running speed.

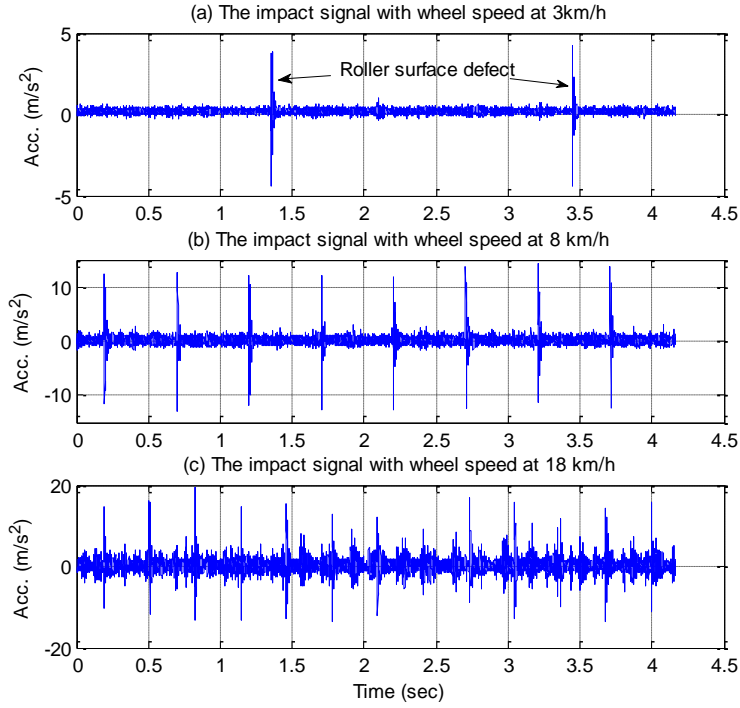


Figure 3 The impact vibration signals caused by roller surface defects under different wheelset running speeds

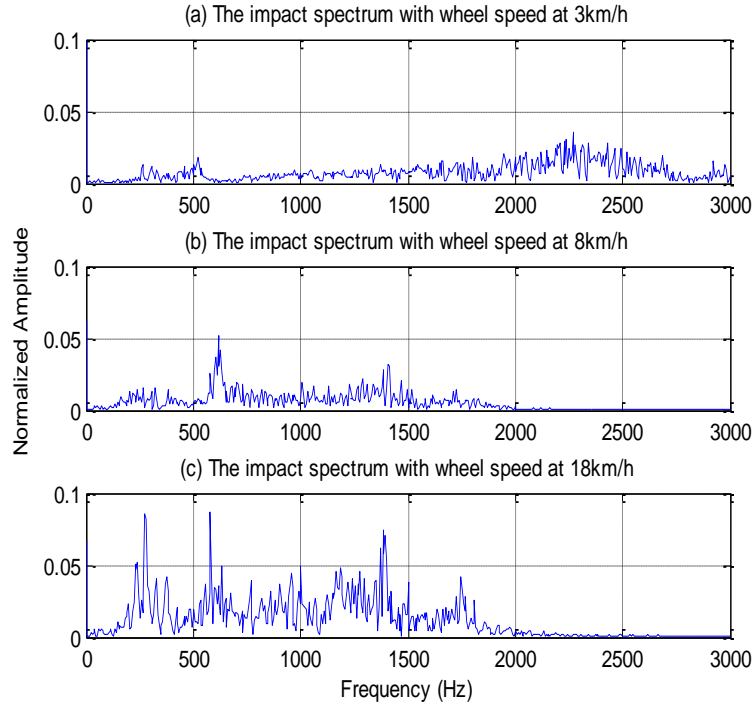


Figure 4 The impact vibration spectra under different wheelset running speeds

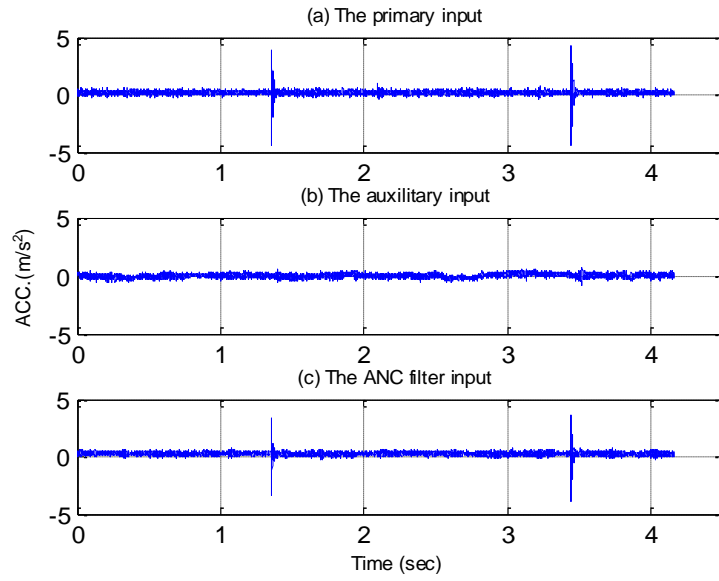


Figure 5 The ANC cancellation effect for wheelset running at 3km/h

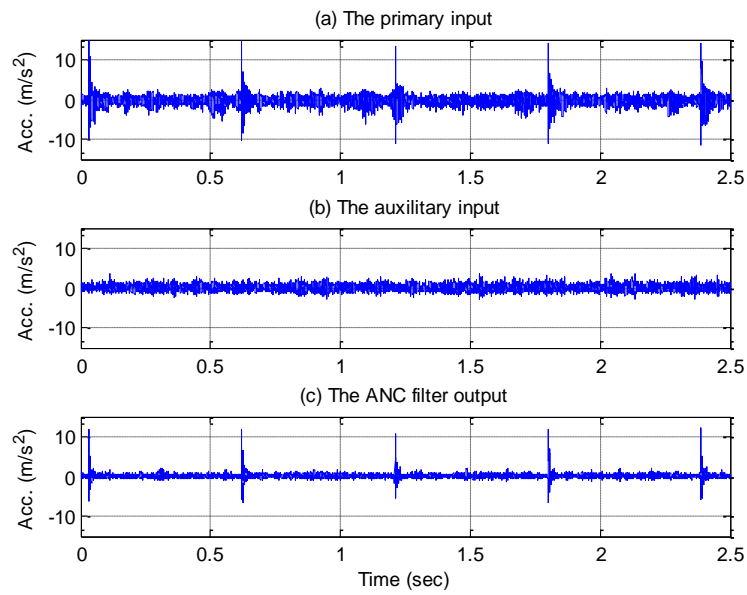


Figure 6 The ANC cancellation effect for wheelset running at 15km/h

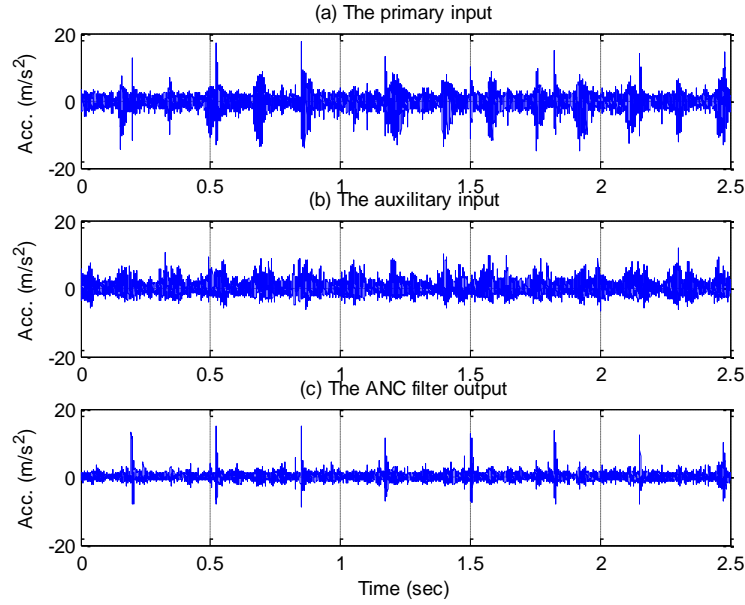


Figure 7 The ANC cancellation effect for wheelset running at 25km/h

A further investigation was made to combine the ANC processing with time-frequency analysis because time-frequency analysis has the advantage of presenting time and frequency information simultaneously. Four time-frequency transform techniques (SPWVT, STFT, CWT and WT) were used for one of impact signals with and without ANC processing. Figure 9 shows the SPWVT result for the impact signal without ANC processing. It can be seen there is an unknown noise exists at about 75ms in time domain and 400Hz in the frequency domain without the ANC processing. However after the ANC processing, the noise was removed and a better and clearer SPWVT result was achieved (figure 10) with the enhanced frequency components at 1.4 kHz for roller surface defect and wheel defect. The same signal was also analysed by STFT and given in figure 11-12. The STFT analysis presents very similar result with SPWVT but with slightly lower resolution in time and frequency domains. The Choi–Williams Transform (CWT) of the impact signal was shown in figure 13-14. Due to the fact the kernel gain does not decrease along the axis in the frequency domain, a rather long smear bar appears with the roller surface defect pulse in the frequency axis. Despite of this disadvantage, CWT can still give a good time and frequency resolution for the roller surface defect signal. Finally wavelet transform (WT) analysis was carried out for the signal with and without ANC processing (figures 15-16). It can be seen that WT demonstrates a good ability to localize the information in time and frequency domains. However because WT is sensitive to noises, figures 15-16 do show some tiny variations caused by random noises.

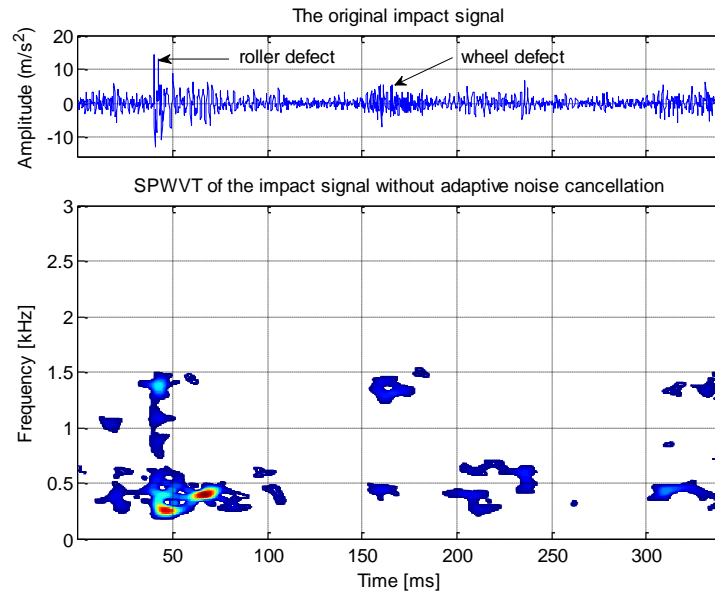


Figure 9 SPWVT of the impact signal without ANC processing

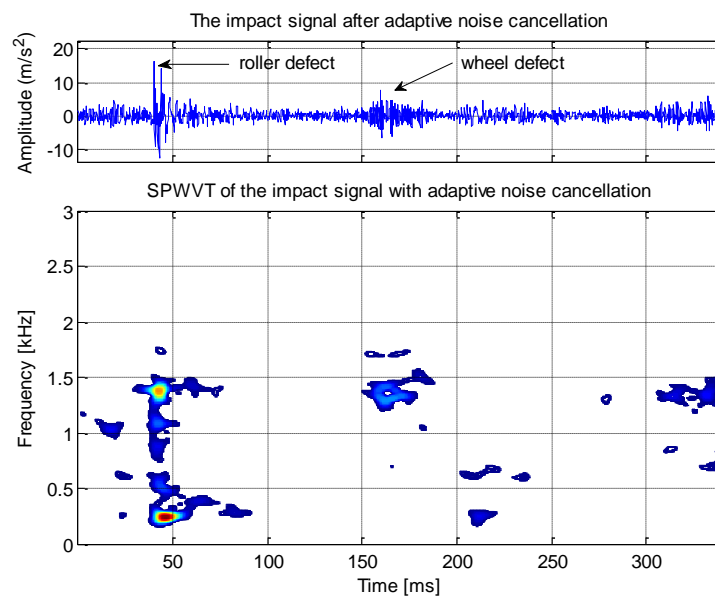


Figure 10 SPWVT of the impact signal with ANC processing



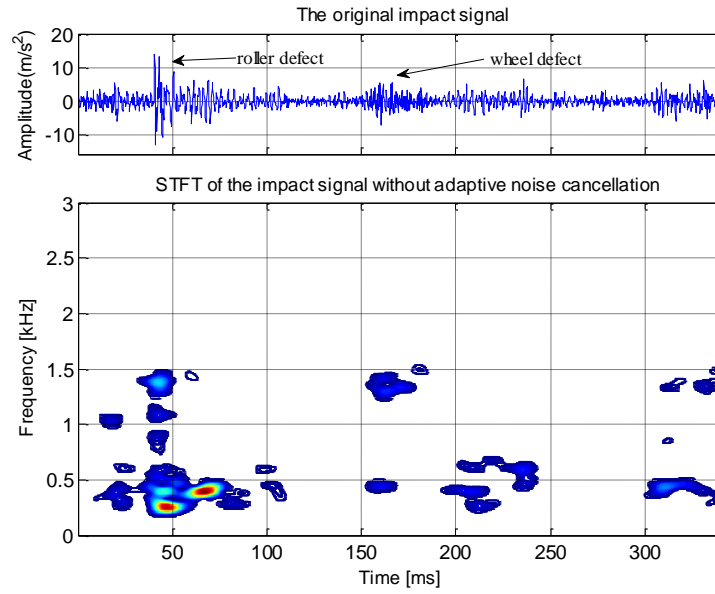


Figure 11 STFT of the impact signal without ANC processing

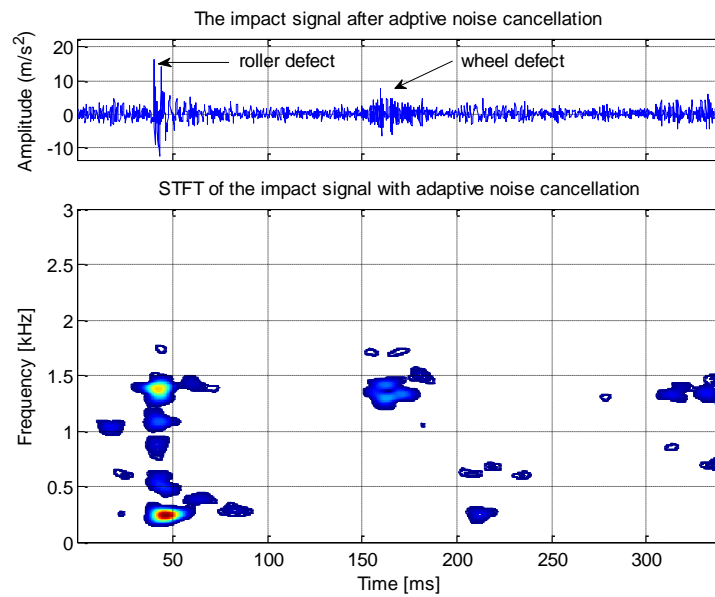


Figure 12 STFT of the impact signal with ANC processing

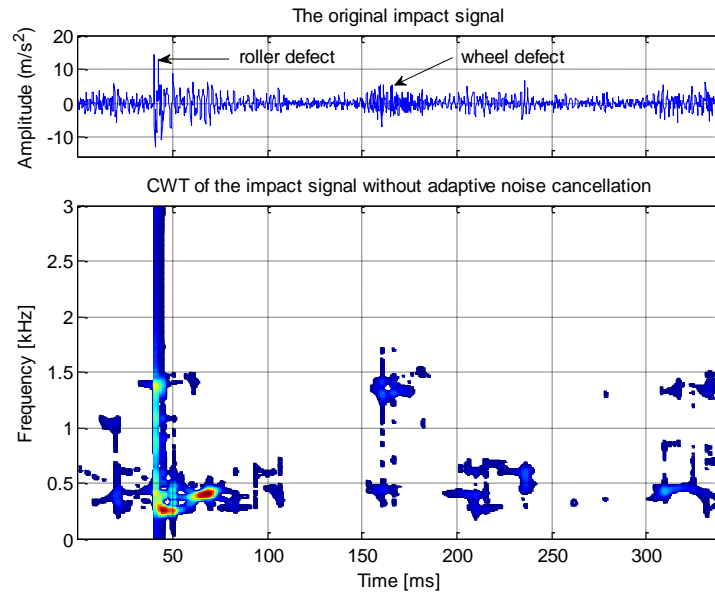


Figure 13 CWT of the impact signal without ANC processing

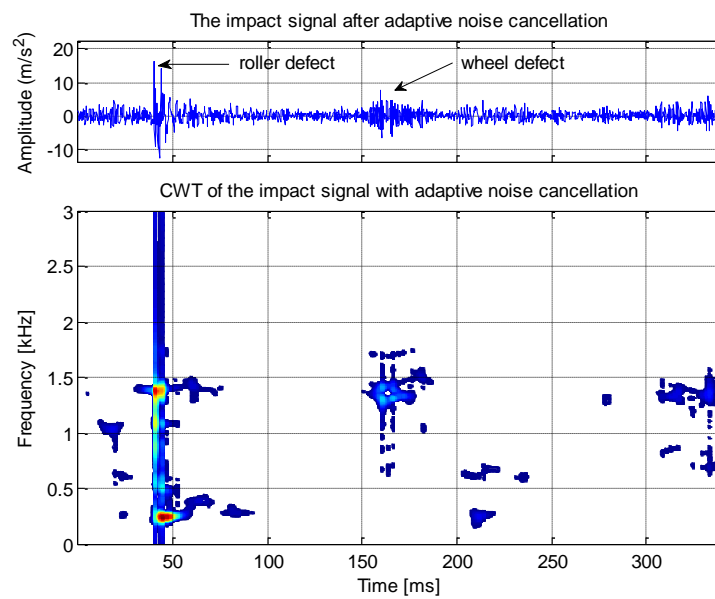


Figure 14 CWT of the impact signal with ANC processing

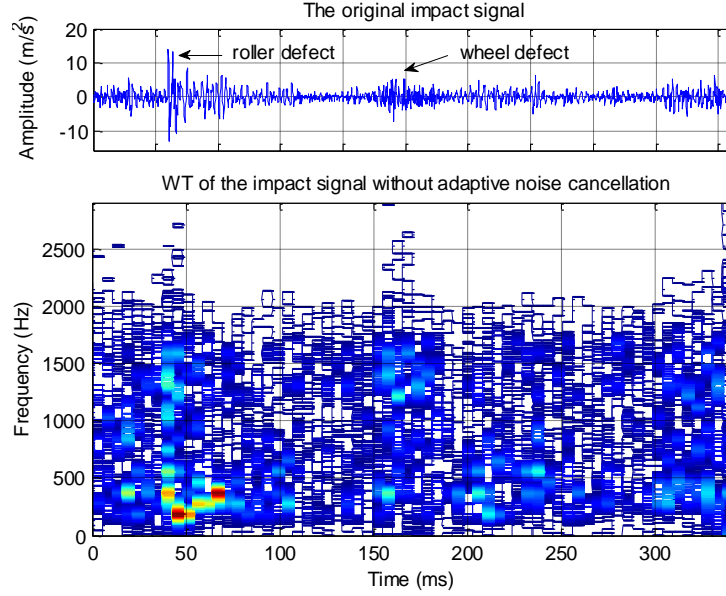


Figure 15 WT of the impact signal without ANC processing

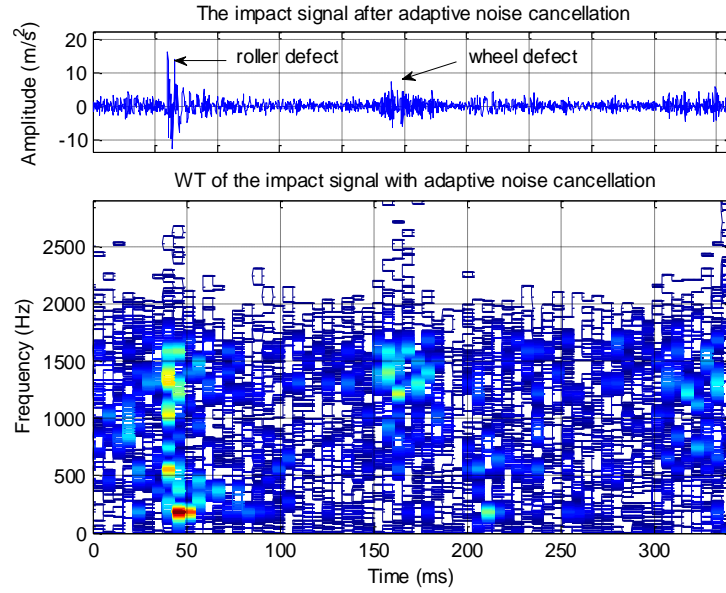


Figure 16 WT of the impact signal with ANC processing

5. Conclusions

In this study, an adaptive noise cancelling (ANC) technique with time-frequency signal processing was proposed to detect rail surface defects. A series of experiments was carried out on a 1/5 scale roller test rig. The experiment results demonstrated that if a wheelset is running at low speed the ANC method is less attractive because of the good original signal-to-noise ratio in the vibration signal. However if a wheelset is running at relatively high speed, there is a significant level of noise presented. For example, the wheel flange contacts between wheel and rail can contaminate the wanted signal caused by rail surface defects and makes the detection difficult. The experiments proved that ANC could be an effective way to eliminate this unwanted noise.

Further investigation about time-frequency analysis techniques was also made for rail surface defects. Four time-frequency analysis methods (STFT, SPWVT, CWT and WT) were tested. The results show all four time-frequency methods can present proper time-frequency information for the vibration generated by wheel flat and rail surface defects. However they have different advantages and disadvantages. The SPWVT gives a better representation with a both time and frequency resolutions while WT shows good localisations in both time and frequency dimensions. STFT presents slightly lower resolutions in time and frequency axes. CWT displays reasonable information of the roller surface defect signal in time and frequency domains but with some smear disadvantage effects in frequency domain caused by its inherited problem. Despite of this drawback CWT is still a good alternate choice for the time-frequency analysis. The combination of the ANC technique and an appropriate time-frequency analysis method like SPWVT and WT may provide a very useful tool for condition monitoring and fault diagnosis in the railway industry.

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