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A novel Doppler Effect reduction method for wayside acoustic train bearing fault detection systems

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ABSTRACT

Wayside acoustic detection of train bearing faults plays a significant role in maintaining safety in the railway transport system. Due to the relative movement between the train and the detection system, the collected acoustic signals are distorted by the Doppler Effect which results in frequency-domain distortion. Combining the multi-scale chirplet path pursuit (MSCPP) method, a variable digital filter (VDF), and a new motion parameter estimation method, a novel Doppler Effect reduction method is proposed. This can be used by wayside acoustic monitoring systems to improve detection system for train bearing faults, as illustrated in this paper. The MSCPP method with the build-in criterions is firstly used to estimate the instantaneous frequencies (IFs) of harmonic components in the wayside acoustic signals. Next, VDFs whose centre frequencies are the fitted IFs are constructed to exclude harmonic components. Using these, residual signals, free of strong harmonic interferences, can be obtained. At the same time, the motion parameters can be obtained by using a recently developed estimation method based on fitted IFs. The residual signal is then resampled to reduce the Doppler Effect by using the resampling time vector constructed using those estimated motion parameters. Finally, any bearing fault features can be extracted using the spectral kurtosis (SK) method. The effectiveness of the proposed signal processing method is verified by simulation and field-based experiments, as demonstrated in this paper.

1. Introduction

Train bearings are a key component of the vehicle that must support the entire weight of the train and operate at high speeds. Faults occurring in train bearings can result in economic loss or even casualties. Hence, fault detection in these key components plays a significant role in maintaining and continuing to increase role of rail in transportation networks. Wayside acoustic detection for train bearings has recently attracted increased attention because one monitoring station will observe multiple vehicles and no physical track access is required in order to install the equipment.

The signals obtained by wayside acoustic monitoring stations are distorted by the Doppler Effect due to the relative motion between the train being inspected and the detection system. The Doppler Effect results in serious frequency-domain distortion to the collected signals, which is an obstacle to train bearing fault detection. Hence, the reduction of the Doppler Effect is a key stage in wayside acoustic train bearing fault detection. The most commonly used methods of Doppler Effect reduction can be classified into two main categories: instantaneous frequency (IF)-based method, and parameter-based method.

The IF-based methods are the combination of instantaneous frequency (IF) extraction and time-domain interpolation resampling (TIR). Central to those methods are accurate IF estimation. Some methods, (e.g. Hilbert transform [1], time-frequency ridge extraction [2]) have been proposed to address this issue. In IF-based methods, the resampling time vector tr is constructed based on the IF generated by the target bearing and its invariant frequency f_o [2,3], as shown in Eq. (1).

$$tr(k) = \sum_{i=1}^{k} \frac{f_o \cdot \Delta t_s}{f_o(t_i)} \tag{1}$$

where k is the resampling point; f_o is the stationary frequency of the signal; $f_o(t)$ is the IF curve which is the variation of f_o caused by the Doppler Effect; and Δt_s is the sampling interval for the raw signal. The advantage of this kind of method is that it is simple to implement while yet effective. However, the resonance frequency of the target bearing is difficult to estimate because of the complex

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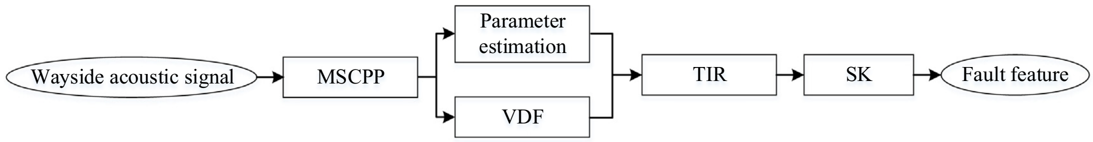

Fig. 1. Simplified flow chart of the proposed method.

structure of the rotational system. Furthermore, Eq. (1) implies two problems: (i) how to find the IFs generated by the target bearing, and (ii) how to estimate the invariant frequency f_o beforehand. Hence, these kinds of methods are rarely applied in practice.

The parameter-based method is a scheme that combines multiple motion parameters and time-domain interpolation resampling. In order to construct the resampling time vector, *tr*, motion parameters for the target bearing are obtained using either velocity sensor based measurements or the matching pursuit method. Using sensor based measurements, the parameters can be obtained in real time [4], but extra sensors will increase cost of the condition monitoring system. To overcome this disadvantage, researchers have proposed methods such as the Dopplerlet transform [5,6] and the single side Laplace wavelet [7] which are based on matching a Doppler distorted correlation model to calculate the motion parameters. In these methods, the construction of *tr* is only based on motion parameters [8,9], as shown in Eq. (2).

$$tr = t + \frac{\sqrt{r^2 + (s - vt)^2}}{c} \tag{2}$$

where r is the distance between the train and the microphone measured perpendicularly to the track; s is the initial distance between the train and microphone measured longitudinally along the track (as shown in Fig. 4); v is the speed of the train (the speed is considered as a constant because the time for a train passing the microphone is short); t is the time within the period of detection; and c is the speed of sound. The performance of those matching pursuit methods has been verified [5–7], however constructing the matching model is a time-consuming process and thus these techniques cannot be applied in real-time condition monitoring systems.

Drawing from the strengths of both the IF and parameter based methods, researchers have proposed a novel Doppler Effect reduction method in which IF extraction and curve fitting, based on the least-squares method, are applied to estimate motion parameters [8,10,11]. The method has been shown to perform well, however the resonant frequencies of the target bearings can be masked by high levels of background noise such as those found in real operating conditions. Additionally, curve fitting based on the least-squares method is complex [12] and may not support real-time operation.

To overcome the above problems, a novel Doppler Effect reduction method is proposed in this paper. The method is a combination of the multi-scale chirplet path pursuit (MSCPP) method, a variable digital filter (VDF), and the new motion parameter estimation method described in [12]. The use of the MSCPP method with the build-in criteria is firstly used to extract the IFs of harmonic components found in wayside acoustic signals. The build-in criteria are used to determinate the births and the deaths of IF curves, and the estimated IFs are then subjected to cubic-spline fitting. Secondly, the fitted curves are set as the centre frequencies of the VDFs which are constructed to exclude the main harmonic components from the collected acoustic signals. Consequently, the residual signal can be obtained. At the same time, a new method, proposed by Timlelt et al. [12] and based on the obtained IFs, is used to estimate the motion parameters. These parameters are then used to construct the resampling time vector, *tr*, as per Eq. (2). The Doppler-free signal can be obtained by resampling the residual signal using the time-domain interpolation resampling (TIR) method. Finally, any bearing fault features can be extracted using the spectral kurtosis (SK) method. The simplified flow chart of the proposed method is shown in Fig. 1.

The sections of this paper are organised as follows: In Section 2, the MSCPP method is introduced. In Section 3, the VDF method is introduced. Motion parameter estimation is introduced in Section 4. A novel Doppler Effect reduction method based on the proposed method is presented in Section 5. In Section 6 and Section 7, the simulation and field experiments demonstrating the proposed method are introduced. The conclusions of this paper are presented in the final section.

2. Multi-scale chirplet path pursuit

The MSCPP method was initially proposed by Candes et al. [13]. The method is based on the estimation of IFs within continuously time-varying component signals. It makes use of a multi-scale chirplet atom whose IF is a straight-line. A brief introduction to the MSCPP method is provided in the following section.

Any signal $\mathrm{f}(t)$ can be represented as a linear combination of a group of atoms $\{\boldsymbol{h}_n\}$, as shown in Eq. (3), where $\boldsymbol{a}_n$ is the index of the n-th atom [14]. If $\{\boldsymbol{h}_n\}$ is orthogonal, then the inner product can be used to compute $\boldsymbol{a}_n$ (Eq. (4)). Hence, $\boldsymbol{a}_n$reflects similarity between the signal $\mathrm{f}(t)$ and the atom $\boldsymbol{h}_n$.

$$\mathrm{f}(t) = \sum_{n \in Z} \boldsymbol{a}_n \boldsymbol{h}_n \tag{3}$$

$$\boldsymbol{a}_n = \langle \mathrm{f}(t), \boldsymbol{h}_n \rangle / \|\boldsymbol{h}_n\| \tag{4}$$

Multi-scale chirplet atoms $\boldsymbol{h}_{a,b,\boldsymbol{I}}(t)$ are used in the MSCPP method, as follows

$$\boldsymbol{h}_{a,b,I}(t) = |\boldsymbol{I}|^{-1/2} e^{-i\left(at^2/2 + bt\right)} \mathrm{l}_{\boldsymbol{I}}(t) \tag{5}$$

where a and b are the slope and offset coefficients respectively and $at + b$ should be less than $f_s/2$ (where f_s is the sampling frequency); $\boldsymbol{I}$ is the dyadic time interval, i.e. $\boldsymbol{I} = \left[k2^{-j}, (k+1)2^{-j}\right]$ where $k = 0, 1, \cdots, \left(2^j - 1\right)$ and $j = 0, 1, \cdots, \log_2(N-1)$, and N is the number of sampling points; $\mathrm{l}_{\boldsymbol{I}}(t)$ is the rectangular window function, which is 1 when $t \in \boldsymbol{I}$ and 0 when $t \notin \boldsymbol{I}$; and $|\boldsymbol{I}|^{-1/2}$ is the normalization factor which makes $\|\boldsymbol{h}_{a,b,I}(t)\|_{L_2} = 1$.

Eq. (5) indicates that the IF of the multi-scale chirplet atom is $at + b$. Hence, the IF of $\mathrm{f}(t)$ can be estimated by linking the linear frequencies of the atoms together piece by piece. The optimal atom in a dyadic time interval can be obtained through calculating the maximum correlation coefficient $\boldsymbol{\beta}_I$ between the atom and $\mathrm{f}(t)$ in the time interval, as shown in Eq. (6).

$$\boldsymbol{\beta}_{\boldsymbol{I}} = \max_{\boldsymbol{I}} \left\langle \mathrm{f}(t), \boldsymbol{h}_{a,b,\boldsymbol{I}} \right\rangle \tag{6}$$

where $\langle \cdot \rangle$ represents the inner product operator. In this case, $\boldsymbol{\beta}_{\boldsymbol{I}}$ contains the amplitude and the initial phase information of $\mathrm{f}(t)$ [15]. Denoting $\mathrm{c}_{\boldsymbol{I}}(t)$ as the representation of the component decomposed in the dyadic interval, this is expressed as shown in Eq. (7).