Mechanical Systems and Signal Processing 90 (2017) 208–221

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

journal homepage: www.elsevier.com/locate/ymssp

Adaptive parameter blind source separation technique for wheel condition monitoring ☆

Jie Zhang [a,*], Hongli Gao [a], Qiyue Liu [a], F. Farzadpour [b], C. Grebe [b], Ying Tian [a]

[a] School of Mechanical Engineering, Southwest Jiaotong University, Chengdu 610031, China
[b] Department of Electrical and Computer Engineering, University of Windsor, Windsor N9B3P4, Canada

ARTICLE INFO

Article history:
Received 27 October 2015
Received in revised form 5 August 2016
Accepted 16 December 2016

Keywords:
Condition monitoring
Blind source separation
Wheel defect
Non-stationary signal
Adaptive time-frequency distributions

ABSTRACT

Wheel condition monitoring has played a key role in the safe operation of railway vehicles. Blind source separation (BSS) is an attractive tool due to its excellent performance in separating source signals from their mixtures when no detailed knowledge of defective sources and the mixing process is assumed. In this paper, we propose an adaptive parameter BSS approach based on the adaptive time-frequency distributions theory in order to deal with the non-stationary blind separation problem and apply it to wheel defect monitoring. Some classical time-frequency signal analysis and BSS methods are applied in comparison with the proposed approach through frequency-varying non-stationary and time-varying non-stationary simulations. Experiments of single and multi-fault wheels have been conducted using the wheel/rail simulation facility to illustrate the effectiveness of the proposed method in processing the non-stationary signals with varying fault complexity.

1. Introduction

The wheel-rail contact is critical to the safe and efficient operation of a railway network. Much of the wheel-rail wear complexity is the result of the constantly varying operating conditions that damage the circular shape of the wheel [1,2]. Common wheel shape errors include flat spots, polygonal wear, tread spalling, etc., as shown in Figs. 1 [3].

Wheel abnormalities reduce the safety of operation and may lead to serious railway accidents [4]. Condition monitoring system is a significant contributor in achieving safety and economy improvements. Real-time detection of wheel defects has been a subject of intense academic research for many years with more practical research throughout the last three decades [5–9]. However, the capabilities of current approaches require further improvement.

Blind source separation (BSS) is an attractive tool in wheel condition monitoring because of the powerful performance of separate source signals from their mixtures when no detailed knowledge of defective sources and the mixing process is assumed. For improvement of feature extraction and information understanding, the following BSS techniques are widely used: independent component analysis (ICA) [10], non-negative matrix/tensor factorization (NMF/NTF) [11], latent variable analysis [12], sparse component analysis [13] and dictionary learning [14]. Most of the BSS approaches focus on stationary

☆ This project is supported by National Natural Science Foundation of China (Grant Nos. 51205323, 51275426 and 51475393) and State Scholarship Fund of China.

* Corresponding author.
E-mail address: lsy55zj@home.swjtu.edu.cn (J. Zhang).

http://dx.doi.org/10.1016/j.ymssp.2016.12.021

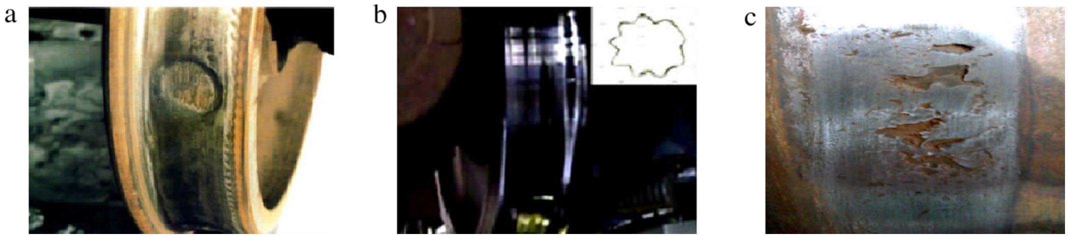

Fig. 1. Wheel shape errors: (a) flat, (b) polygonal wear and (c) tread spalling.

sources separation, and some approaches which are able to deal with non-stationary problem have been proposed, such as learning mixtures of ICAs [15] and frequency domain statistics [16].

In this paper, we propose a new non-stationary BSS approach. The applicability of our approach is verified through wheel condition motoring simulations and experiments. The remainder of the paper is organized as follows. In Section 2, the conventional time-frequency signal analysis method and classical BSS methods are used in frequency-varying non-stationary and time-varying non-stationary simulation experiments. Also, the limitations and difficulties associated with existing wheel condition monitoring methods are illustrated. In Section 3, a new non-stationary BSS approach based on the adaptive time-frequency distributions theory is proposed. In Section 4, the testing of wheels with single and multi-fault are discussed. Section 5 summarizes the entire work.

2. Existing methods

Since the 1970s, on-line defect detection of wheel tread through electrical signal methods, displacement measurements and vibration acceleration methods has been studied globally. Broadly speaking, there are two types of monitoring system: infrastructure-based monitoring and rolling-stock-based monitoring [17]. This article examines monitoring based on vibration measurements made by acceleration sensors which detect wheel defect information produced by the impact of the wheel and rail. The responses are then processed through signal processing techniques to identify possible existing wheel defects. The difficulty of accurate defect diagnosis is illustrated in the following simulation experiments.

2.1. Simulation experiment 1: Time-frequency analysis

Usually, a high-speed train exceeds speeds 200 km/h on straight lines and has speed restrictions of less than 100 km/h on curves. In this subsection, we design a group of simulation signals with the frequency-varying non-stationary characteristic corresponding to the change of train speed.

Fig. 2 shows a set of wheels. The left worn wheel is with a multi-fault, flat spot and tread ellipse. Fig. 3 shows the signals resulting from wheel-rail contact vibrations as the train with the worn wheel accelerates and then decelerates. The first s_1 is a frequency-varying sine signal corresponding to the wheel ellipse. The second s_2 is a frequency-varying impulse signal corresponding to the flat spot. The third s_3 is a low-frequency sine signal corresponding to the long wave trend of the rail, and the fourth s_4 is a Gaussian random signal corresponding to the wheel-rail surface roughness. In this paper, the mixture model we adopted is a linear instantaneous mixture of independent sources. The rationality of this model is verified by experiments in Section 4. Fig. 4 shows the mixtures observed in these non-stationary source signals x_1 to x_4.

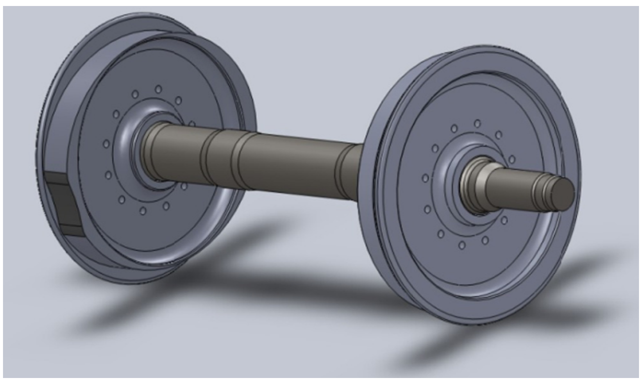

Fig. 2. Flat spot and ellipse of wheel tread.