Chaos, Solitons and Fractals 89 (2016) 27–39

Contents lists available at ScienceDirect

Chaos, Solitons and Fractals

Nonlinear Science, and Nonequilibrium and Complex Phenomena

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

A new nonlinear blind source separation method with chaos indicators for decoupling diagnosis of hybrid failures: A marine propulsion gearbox case with a large speed variation

Zhixiong Li [a,b,*], Z Peng [b]

[a] School of Mechatronic Engineering & Jiangsu Key Laboratory of Mine Mechanical and Electrical Equipment, China University of Mining & Technology, Xuzhou 221116, China

[b] School of Mechanical & Manufacturing Engineering, University of New South Wales, NSW 2052 Sydney, Australia

ARTICLE INFO

Article history:
Available online 9 October 2015

Keywords:
Marine propulsion gearbox
Hybrid faults
Fault decoupling
Chaos indicator
Morphological component analysis

ABSTRACT

The normal operation of propulsion gearboxes ensures the ship safety. Chaos indicators could efficiently indicate the state change of the gearboxes. However, accurate detection of gearbox hybrid faults using Chaos indicators is a challenging task and the detection under speed variation conditions is attracting considerable attentions. Literature review suggests that the gearbox vibration is a kind of nonlinear mixture of variant vibration sources and the blind source separation (BSS) is reported to be a promising technique for fault vibration analysis, but very limited work has addressed the nonlinear BSS approach for hybrid faults decoupling diagnosis. Aiming to enhance the fault detection performance of Chaos indicators, this work presents a new nonlinear BSS algorithm for gearbox hybrid faults detection under a speed variation condition. This new method appropriately introduces the kernel spectral regression (KSR) framework into the morphological component analysis (MCA). The original vibration data are projected into the reproducing kernel Hilbert space (RKHS) where the instinct nonlinear structure in the original data can be linearized by KSR. Thus the MCA is able to deal with nonlinear BSS in the KSR space. Reliable hybrid faults decoupling is then achieved by this new nonlinear MCA (NMCA). Subsequently, by calculating the Chaos indicators of the decoupled fault components and comparing them with benchmarks, the hybrid faults can be precisely identified. Two specially designed case studies were implemented to evaluate the proposed NMCA-Chaos method on hybrid gear faults decoupling diagnosis. The performance of the NMCA-Chaos was compared with state of art techniques. The analysis results show high performance of the proposed method on hybrid faults detection in a marine propulsion gearbox with large speed variations.

1. Introduction

Currently, diesel engines have been used as a power source in propulsion systems in more than 90% of vessels [1]. For high-speed diesel engines, the multi-stage gearboxes are adopted to reduce the engine speed for the propellers. Harsh working environment in the sea accelerates the wear process of key components in the propulsion systems. According to Swedish Club Highlights [2,3], the most vulnerable part of a ship is the marine propulsion system (including the diesel engines), in which the gearboxes are identified as one of the most frequent failure components in the marine propulsion systems [4]. A simple failure, such as worn gears, would

* Corresponding author at: School of Mechatronic Engineering Jiangsu, Key Laboratory of Mine Mechanical and Electrical Equipment, China University of Mining Technology, Xuzhou 221116, China. Tel.: +61 0451069970.
E-mail address: zhixiongli@cumt.edu.cn (Z. Li).

http://dx.doi.org/10.1016/j.chaos.2015.09.023

knock off the whole propulsion system during a journey and hence would significantly threat the ship safety. Since the operational reliability and safety is a crucial issue for ships, it is imperative to monitor the condition of the marine propulsion systems for the purpose of condition-based maintenance (CBM) [5–8]. Although literature reports variant technologies and applications for fault detection in gearboxes, such as the Chaos indicators [9–12], the diagnosis of hybrid faults is still a difficult task [13–15]. This is because in practice hybrid faults often occur simultaneously in the same and/or different components of gearboxes [3]. The nonlinear mixing of the hybrid fault vibration characteristics makes it very difficult to correctly detect all the faults using vibration analysis [16]. Also, because of strong background noise, the faults information is smeared in both time and frequency domains and hence it is prone to omit one or more faults in the hybrid fault detection. To improve the reliability and accuracy of the hybrid faults detection, the intelligent classifiers were introduced into the field. The fault detection is then transformed into the pattern recognition problem which can be solved using artificial neural network (ANN) [17], support vector machine SVM [18], or fuzzy inference [19]. These machine learning methodologies could generate satisfactory diagnosis results only if suitable and adequate training samples are provided; however, it is often a challenge to obtain sufficient training data [3]. Alternatively, recent publications show greatly increasing interest in decoupling hybrid faults [20–25]. The vibration signals of hybrid faults are decomposed into sub-signals corresponding to each single fault. By analyzing the sub-signals, the hybrid faults could be identified one by one. The advantage of this kind hybrid faults decoupling is that this approach is more understandable to engineers than pattern recognition because the vibration insight of each fault in the hybrid faults is detailed analyzed and presented. In [20], the multiwavelets transform was adopted to decompose the vibration signal of hybrid faults into wavelet sub-band signals. Then by performing envelop demodulation, the fault vibration characteristics were discovered in the sub-band signals and every fault in the hybrid faults was correlated to one sub-band signal. In [21], the dual-tree complex wavelet was used to decompose the original vibration of the hybrid faults into different wavelet sub-bands. Then the frequency information was found in different frequency bands in the wavelet sub-bands. Similarly, in [22] the original vibration of the hybrid faults was decoupled into several intrinsic mode functions (IMFs), and in [23] order tracking demodulation was employed to decouple the hybrid faults into single fault order signals. These methods were developed and applied to one channel sensor, so their decoupling performance would be influenced by the installation of the sensor. To improve the utilization of sensor information, the blind source separation (BSS) algorithms were developed when multi-channel sensors are used. Two BSS algorithms, that is, the independent component analysis (ICA) [24] and morphological component analysis (MCA) [25], were employed to decouple hybrid fault into single fault vibration source components. However, both the ICA and MCA are based on the linear BSS model, which cannot be applied to all operation conditions of the machine [16,25], such as the run up/coast down condition [26–28]. In fact, in practice the gearbox vibration is often described as the nonlinear mixture of vibration sources of gear meshing, bearings, couplers and shafts [5]. A nonlinear BSS model is much more suitable than the linear one for analyzing the gearbox vibration signals for fault diagnosis under a large speed variation condition [29]. Unfortunately, very limited work has reported the hybrid faults decoupling diagnosis with a large speed variation. A promising strategy to extend the linear BSS into nonlinear framework is the kernel trick [30], that is, to project the original data into the reproducing kernel Hilbert space (RKHS). The kernel trick was introduced into ICA to propose the so-called kernel ICA (KICA), which is able to deal with nonlinear mixtures in the BSS. However, both ICA and KICA require statistical independence between the source signals. In vibration analysis, the vibration sources excited by the machine components are often statistically dependent, which limits the applications of ICA and KICA. In order to broaden the application of linear BSS, the sparse representation and decomposition [31] were introduced into BSS to enhance the separation performance. Zibulevsky and Pearlmutter [31] showed that based on the sparse decomposition the BSS quality was greatly improved by the sparse component analysis (SCA) against classical ICA algorithms. Further, the MCA extends the signal dictionary of SCA into multiply dictionaries. Thus, the MCA is able to decompose a signal in the sparse space from different aspects using multiply dictionaries and the possibility of the same sparse representation function on two different sources is extremely low. So even when the sources are not statistically independent, they can probably be decomposed into different sparse functions because the functions in the dictionaries are allowed to not be linearly independent [31]. As a result, the MCA can be applied to applications that the SCA and ICA have difficulties. Chen et al. [32,33] showed better performance of the MCA against the ICA in mechanical fault diagnosis. Recently, Li et al. [25] demonstrated that the MCA outperformed the ICA in hybrid fault diagnosis in the stable driving speed condition of the gearbox. It is worth extending the linear MCA into a nonlinear model to solve the hybrid faults detection under a speed variant condition. Sharing the light of the KICA, it is possible to implement the MCA in the RKHS to form the new nonlinear MCA algorithm. The key issue of nonlinear MCA is to construct a suitable strategy to project the original vibration data into the RKHS. Fortunately, the graph embedding based kernel spectral regression (KSR) [34] provides a powerful framework for data mining in RKHS. Intrinsic discriminant structure hidden in the original data could be efficiently discovered by the KSR in RKHS. Previous work showed that it was flexible to incorporate the KSR with variant algorithms [35–37]. Compared with existing kernel strategies, such as Baths kernel trick [30], the out-of-sample extension problem could be solved with less computation by the KSR in the kernel mapping space [30]. In addition, the KSR adopts the L_1-norm regularizer to efficiently compute the sparse projections of the original data in RKHS [37]. Considering that the MCA analyzes signals through sparse representation and decomposition, it is naturally to establish the nonlinear MCA model under the KSR framework in the sparse space. The KSR based nonlinear MCA would be hence very economical in computation complexity, which would be beneficial for the mechanical fault diagnosis. In order to address the hybrid faults decoupling with a large speed variation in gearboxes, this paper