Journal of Sound and Vibration 432 (2018) 569–601

Contents lists available at ScienceDirect

Journal of Sound and Vibration

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

Blind deconvolution based on cyclostationarity maximization and its application to fault identification[☆]

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A R T I C L E I N F O

Article history:
Received 6 February 2018
Revised 23 May 2018
Accepted 23 June 2018
Available online XXX

Keywords:
Blind deconvolution
Rayleigh quotient optimization
Cyclostationary criterion
Cyclostationary signals
Fault identification

A B S T R A C T

Blind deconvolution algorithms prove to be effective tools for fault identification, being able to extract excitation sources from noisy observations only. In this scenario, the present paper introduces a novel blind deconvolution method based on the generalized Rayleigh quotient and solved by means of an iterative eigenvalue decomposition algorithm. This approach not only is characterized by a weighting matrix that drives the deconvolution process, but can also be easily adapted to arbitrary criteria. Based on this framework, a novel criterion rooted on the maximization of the cyclostationarity of the excitation – as typically encountered with machine faults – is proposed and compared with other blind deconvolution methods existing in the literature. The comparisons involve both synthesized and real vibration signals, taking into account a gear tooth spall and an outer race bearing fault. The results reveal superior capability to recover impulsive cyclostationary sources with respect to other blind deconvolution methods, even in the presence of impulsive noise or under non-constant speed.

1. Introduction

The identification of impulsive faults is of major importance in the diagnosis of rotating machines, especially for gears and bearings which usually are the most critical components in many mechanical systems. The identification of incipient faults can be difficult, particularly in the early stage, since the impulsive pattern due the fault occurrence is often masked by background noise and other interferences. The situation is further worsen by the spreading effect of the unknown transmission path. For this purpose, blind deconvolution (BD) techniques can recover the impulsive pattern from noisy observations, even considering the effect of an unknown linear time-invariant system.

In the field of seismic signal processing, Wiggins [1] pioneered BD by developing an iterative algorithm based on the maximization of the kurtosis (called Varimax in his paper) in order to recover a spike-like source from a signal convolved with an unknown impulse response function (IRF). In the same field, Cabrelli [2] proposed another criterion, called D-Norm, geometrically equivalent to the Varimax norm, which poses a direct solution to BD. This method has been recently refined by McDonald and Zhao [3]. In the literature, these BD methods are known as minimum entropy deconvolution (MED) and optimal minimum entropy deconvolution adjusted (OMEDA), respectively. Other authors explored higher-order statistics as well as different optimization algorithms. Lee and Nandi [4] analyzed the performance of BD via higher-order statistics considering impacting signals from a vibrating cantilever beam. The same authors [5] demonstrated also that the objective function method (OFM),

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https://doi.org/10.1016/j.jsv.2018.06.055
0022-460X/

Nomenclature

AR	Auto-regressive
BD	Blind deconvolution
CS1	First-order cyclostationarity
CS2	Second-order cyclostationarity
CYCBD	Maximum second-order cyclostationarity blind deconvolution
EVA	Eigenvalue algorithm
ICS	Indicators of cyclostationarity
IQR	Interquartile range
IRF	Impulse response function
MCKD	Maximum correlated kurtosis deconvolution
MED	Minimum entropy deconvolution
MOMEDA	Multipoint optimal minimum entropy deconvolution adjusted
OFM	Objective function method
OMEDA	Optimal minimum entropy deconvolution adjusted
SIMO	Single-input-multi-output
SISO	Single-input-single-output

that has been exploited in MED and OMEDA, and the eigenvalue algorithm (EVA) give equivalent results considering the same experimental measurements. Another statistics that combines both skewness and kurtosis (called Jarque-Bera statistic) has been investigated by Obuchowski et al. [6] for the gear fault identification. The reader should be aware that the general problem posed by BD actually embraces a wide range of applications, such as image processing, telecommunications and seismic, and therefore a number of BD methods can be found in the literature [7]. However, this research work is focused on rotating machine diagnosis and only the BD methods that proved to be effective in this application will be considered. Among all these blind deconvolution methods, MED has been the most commonly used for machine fault identification. MED has been typically exploited in combination with other signal processing techniques in order to improve its performance for machine diagnosis since it recovers preferably a large single peak rather than a train of impulses, as typically encountered with machine faults. Regarding tooth faults, Endo and Randall [8] exploited MED in order to improve detection based on auto-regressive (AR) models. This method has been further investigated by Endo et al. [9] for discriminating a gear tooth spall from a cracked tooth. A similar approach has been proposed by Sawalhi et al. [10] with regard to bearing fault diagnosis, taking advantage of the envelope spectrum driven by maximum spectral kurtosis. In a different way, the spectral kurtosis has been exploited also by He et al. [11] in order to extract multiple bearing faults.

The need of criteria dedicated to machine diagnosis led to the introduction of the correlated kurtosis and the Multi-Point D-Norm. The maximum correlated kurtosis deconvolution (MCKD), has been introduced by McDonald et al. [12] whereas the multipoint optimal minimum entropy deconvolution (MOMEDA), has been proposed by McDonald and Zhao [3]. [A]MCKDMaximum correlated kurtosis deconvolution [A]MOMEDAMultipoint optimal minimum entropy deconvolution adjusted Both criteria try to enhance the vibration signal impulsiveness linked to a specified fault period overcoming the tendency of MED and OMEDA to recover a single dominant impulse.

Although the pivotal role of cyclostationarity in machine diagnosis has been widely recognized [13], it has not yet been applied explicitly in BD criteria for machine fault identification. In this scenario, just one cyclostationary criterion can be found in the literature devoted to vibration-based fault diagnosis, i.e. the MCKD [12], while the others are based on extracting the most impulsive contribution (MED [1] and OMEDA [2]) or a periodic impulse train (MOMEDA [3]). Despite MCKD being cyclostationary criterion, it has been proposed empirically, without explicit mention of cyclostationarity. Moreover, the criterion at the base of MCKD (called correlated kurtosis) entails some disadvantages that limit its use in many real applications, such as the definition of the number of shifts and the fact that the estimation of the cyclic frequency related to the fault must be very accurate. Moreover, the correlated kurtosis have been proposed empirically without investigations about its statistical properties. Therefore, this research work tries to fill this gap by proposing a simpler and more effective criterion grounded on the cyclostationary framework.

A preliminary overview of standard BD criteria is given, pointing out some original considerations highlighting advantages and limits. In particular, with regard to MED, the relationship between kurtosis and differential entropy is clarified. OMEDA and MOMEDA have been reviewed providing an original interpretation connecting the non-iterative solutions of these two methods to (linear) least square solutions. Concurrently, a qualitative justification of why MCKD is based on a cyclostationary criterion is provided as well. Then, an iterative eigenvalue algorithm for BD of single-input-single-output (SISO) systems based on the generalized Rayleigh quotient is presented as well as its version for single-input-multi-output (SIMO) systems. This algorithm differs from the EVA introduced by Jelonnek et al. [14] by the fact that it is not restricted to the use of fourth-order (cross) cumulants. Furthermore, the deconvolution is guided by a weighting matrix that can be easily modified adapting the deconvolution algorithm to arbitrary criteria. The proposed BD method has been formulated by considering the maximization of higher-order statistics and the cyclostationarity through the indicators of cyclostationarity (ICS). The latter formulation represents the core of this paper. The BD method based on the maximization of the second-order cyclostationarity, called CYCBD, is formulated for both time-dependent signals and for angle-dependent signals; the latter case is particularly useful for rotating machine diagnosis considering non-constant regimes. The CYCBD performance is compared with other BD methods, taking into account five cyclostationary synthesized signals. The simulated results demonstrate the capability of CYCBD to recover impulsive cyclostationary sources at constant and non-constant regimes. In support of the simulated results, two applications have been investigated regarding the identification of a gear tooth spall and an outer-race bearing fault. The experimental results highlight the