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Detection of faults in rotating machinery using periodic time-frequency sparsity

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ABSTRACT

This paper addresses the problem of extracting periodic oscillatory features in vibration signals for detecting faults in rotating machinery. To extract the feature, we propose an approach in the short-time Fourier transform (STFT) domain where the periodic oscillatory feature manifests itself as a relatively sparse grid. To estimate the sparse grid, we formulate an optimization problem using customized binary weights in the regularizer, where the weights are formulated to promote periodicity. In order to solve the proposed optimization problem, we develop an algorithm called augmented Lagrangian majorization–minimization algorithm, which combines the split augmented Lagrangian shrinkage algorithm (SALSA) with majorization–minimization (MM), and is guaranteed to converge for both convex and non-convex formulation. As examples, the proposed approach is applied to simulated data, and used as a tool for diagnosing faults in bearings and gearboxes for real data, and compared to some state-of-the-art methods. The results show that the proposed approach can effectively detect and extract the periodical oscillatory features.

1. Introduction

Condition monitoring and fault diagnosis of rotating machines are of great importance to prevent machinery breakdown in numerous industrial applications. Vibration signals generated by faults in rotating components have been widely studied. Detecting and extracting transient vibration signatures are of vital importance for vibration-based detection of faults in rotating machinery. However, the observed vibration signals are usually corrupted by very heavy background noise [1,2]. Many diagnostic techniques have been developed to extract the fault features based on different transforms, such as short time Fourier transform (STFT) [3–7] and wavelet transform [8–16]. Some methods use morphological decomposition methods, such as empirical mode decomposition (EMD) [17,18], or demodulation [19–21]. Some methods combine conventional time–frequency analysis with other techniques suitable for transients detection, such as bispectrum-based method [22,23] and spectral kurtosis (SK) based methods [24–27].

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The use of sparse representations for fault detection was initially illustrated in Ref. [3], where basis pursuit denoising (BPD) [28,29] was adopted to exploit the sparsity of vibration signals in different domains in order to detect and extract fault features. In Ref. [7], the author considered a morphological component analysis (MCA) problem [30–32], which is a sparsity-based decomposition approach, to improve the extraction of fault features. In Ref. [33] matching pursuit (MP) [34] was used on a customized dictionary to extract oscillatory fault features. In Ref. [35], a sparse representation using the tunable Q-factor wavelet transform [36,37] is utilized to extract oscillatory fault features. Most recently, sparse coding techniques are introduced for fault feature extraction [38].

The periodicity (also called fault characteristic or fundamental frequency in some cases) of potential fault features is very important information for fault diagnosis. In many cases, this information can be simply obtained using the geometry of the specific components under steady rotating speed, or directly obtained from the user operation manual. It is already required as necessary information in many fault diagnosis methods [8,20,39,40]. Some fault diagnosis methods use periodicity information as a verification step after feature extraction (e.g. [41,7]), and some methods use it to determine an optimal frequency band when extracting the oscillation frequency of the fault feature [20,39,40]. Only a few very recent works use the temporal periodic structure to extract fault features [42,43].

The overlapping group sparsity (OGS) approach has been discussed in [44,45], where a multidimensional group structure has been modeled in various domains and convex optimization problems have been formulated, to take advantage of group behavior (e.g. coefficients in STFT domain) to recover signals from noisy observations. Using OGS to extract fault features was introduced and formulated as a convex optimization problem in [43], in which the fault features are assumed to be a periodic sequence of pulses. In addition, it was shown that the objective function can be convex even if some specified non-convex penalty functions are used to promote sparsity. Moreover, when the periodicity information is known, a binary-weighted group structure was used in the regularization, capturing the period of the potential fault features.

In this work, we consider the problem wherein the fault features are comprised of a sequence of oscillatory transients, and sparsity should be promoted in the time–frequency domain. The discrete-time vibration observation y is modeled by

$$y = x + w, \tag{1}$$

where x is an approximately-periodic sequence of oscillatory transients where the period is determined by the characteristic frequency of potential faults, and w is additive Gaussian noise. Moreover, we assume that the oscillation frequencies of the transient component x are unknown but relatively sparse, and the periodicity is over the time domain.

Under the signal model, we seek a solution to the optimization problem

$$c^{\star} = \arg\min_{c} \left\{ F(c) = \frac{1}{2}\|y - Ac\|_2^2 + \lambda \Phi(c) \right\}, \tag{2}$$

for the purpose of extracting the fault feature $x \in \mathbb{R}^N$, where c denotes the coefficients corresponding to an overcomplete transform A of x, where $x = Ac$, and $\lambda > 0$ is a regularization parameter and Φ is a sparsity-promoting penalty function (regularizer) in the domain of c. This paper aims to extract the oscillatory fault features as periodically structured groups of coefficients in the time–frequency domain. We set the operator A to be the normalized inverse STFT, and the function Φ is customized to capture the periodicity in the STFT domain.

To solve a relatively complicated sparsity-based optimization problem, where an iterative scheme has to be adopted, methods are usually based on two algorithms. One is based on majorization–minimization (MM) [46–48], such as the algorithms given in [46,49–53], and further the method of iterated soft-thresholding algorithm (ISTA) [54,55] can be considered as a special case of MM as well (majorizing data fidelity term based on Lipschitz constant). Another trend is based on alternating direction method of multipliers (ADMM) [56,57], and its extension such as split augmented Lagrangian shrinkage algorithm (SALSA) [58], and some recent applications using such algorithm are presented in [59,37].

Some algorithms can be explained as a combination of ADMM and MM as a special case. For instance, a specific function of Bregman distance was described in [60], which is similar to a majorizer, utilized to derive an iterative method for total variation problem [61]. Such concept has been used on total variation problem with multiple extensions such as combinations with wavelet-based denoising, compressive sensing [62–64]. Moreover, the Bregman distance function in [60] was used in other iterative algorithms for convex problems as well, such as the methods proposed in [65,66]. Some recent work in the field of optimization also consider this problem. In [67], a framework is given that instead of using the Bregman distance function in [60], but using proper ‘indefinite proximal terms’ to majorize augmented Lagrangian, the resulting majorized ADMM-style algorithm will converge for convex problem. Moreover, in [68], an ADMM-style algorithm with an embedded criteria’ checking step is proposed based on majorizing the corresponding augmented Lagrangian as well. Additionally, in [69], a scheme of majoring a cross term with the ADMM-style iteration is proposed for convex problem.

In this work, we propose an algorithm that combines ADMM and MM with a more general and simpler formulation, based on block successive upper-bound minimization (BSUM) algorithm [70]. Moreover, the algorithm allows non-convex regularization to promote the resulting sparsity, and it is guaranteed to converge to a local minimum even though the objective function is not convex.