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Compressed sparse time–frequency feature representation via compressive sensing and its applications in fault diagnosis

Yanxue Wang [a,*], Jiawei Xiang [b], Qiuyun Mo [a], Shuilong He [a]

[a] School of Mechanical Engineering, Guilin University of Electronic Technology, Guilin 541004, PR China
[b] College of Mechanical and Electrical Engineering, Wenzhou University, Wenzhou 325035, PR China

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ABSTRACT

Feature extraction in time–frequency domain is wildly used in fault diagnosis of rotating machines. However, it needs more time and space to store the time–frequency information, which restricts its practical applications, especially for remote health monitoring. A novel parallel FISTA-like proximal decomposition algorithm was proposed for reconstruction of sparse time–frequency representation (TFR) from the limited noisy observations based on the recently developed compressive sensing. The effectiveness of recovering buried sparse signatures was demonstrated by numerical simulations. The proposed method yielded better results than those obtained by the traditional RecPF method. A novel framework for remote machine health condition monitoring was then developed via the proposed algorithm and the advancements in wireless communication. The effectiveness of the new proposed method for the sparse TFR in detecting bearings and gears defects in rotating machines is further verified using many practical cases. These results illustrate the proposed method can well retain TF signatures without clearly artifacts in the recovered TFR using only very limited measurements.

1. Introduction

Time–frequency representation (TFR) has been a field of active research in the last few decades and remains so today. A precise and fine representation of nonstationary signals in the time–frequency domain is of great importance in many fields, and especially in mechanical fault diagnosis. Traditional TFRs represent energy or power of signals in two-dimensional functions of both time and frequency, which accurately reveal fault signatures in diagnostics. Currently, different TFR uses different kernel function, for example, the short-time Fourier transform (STFT) which has a linear kernel, the Wigner–Ville distribution (WVD) which has a quadratic kernel and the wavelet transform which uses an analysis basis of signals constrained in both time and frequency. Most of these TFRs have been successfully applied to waveform data analysis in fault diagnosis of gear, bearings and other mechanical systems [1]. The WVD is one of the most popular quadratic TFRs, which distributes the energy of the signal over time and frequency, offering good time–frequency localization and preserving time–frequency shifts. In order to alleviate the undesired effect of the quadratic cross-terms, variants of the original WVD based on smoothing in frequency and/or time have been proposed: the smoothed-pseudo Wigner–Ville distribution (SPWVD). SPWVD was recently used in the time–frequency manifold correlation matching for periodic fault identification in rotating machines [2]. Choi–Williams distribution overcomes the drawbacks of the STFT and Wigner distribution, and provides high resolution in time and frequency while suppressing

* Corresponding author. Tel./fax: +86 0773 2290108.
E-mail address: Yan.xue.wang@gmail.com (Y. Wang).

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interferences. Choi–Williams reduced interference time–frequency distribution was also utilized in machinery diagnostics [3]. In addition, some data-driven signal decomposition methods were developed to construct the third time–frequency category, such as local mean decomposition [4,5] and empirical mode decomposition [6].

TFR provides potentially strong features for the nonstationary signal analysis. TFR is generally represented as a two-dimensional grey-scale/color picture, where one axis represents time and the other represents frequency while the grey/color values represent the energy at a specific instant in time and frequency band. However, these representations contain a huge amount of information, for example, for a 64-ms signal with the sampling frequency of 16 kHz, the TFR with a resolution of $512 * 1024$ will contain 524,288 TF samples. Due to the computational complexity issues, the application of such a huge amount of data in practical applications is impossible, especially for remote transmission and real-time applications. Additionally, not all the information in a TF plane represents the signatures of the measured signals. Therefore, in order to make a TFR more suitable for any diagnosis application, it is essential to record TFR while removing the redundant information as much as possible.

Due to increased automation, fast sampling rates and advantages in computing power, data increase daily. There is also a need for approaches that can reduce the real-time burden on the data saving and remote diagnostics. Some techniques have been recently proposed to compress signals in time domain based on a transform approach. Marius et al. proposed compression method for mechanical vibration signals which was based on the orthogonal transform decomposition into a large number of subbands [7]. Guo et al. developed a signal compression method based on the optimal ensemble empirical mode decomposition for bearing vibration signals [8]. Another method for rotating mechanical vibration compression using a two-dimensional lifting wavelet transform was developed in [9], which converted periodical vibration data from one-dimensional to two-dimensional in order to reduce the dependency both within a single cycle and across cycles. However, all these methods are only developed to compress temporal signals. The compression has never conducted in the time–frequency domain in the fields of the practical applications of machine diagnosis.

Compressed (compressive) sensing (CS) was a recently proposed framework that enables the recovery of a sparse signal from a few of its measurements by exploiting the sparsity as the prior knowledge of the original signal. Most of CS-based applications lie in computational photography and seismic data processing. CS was first adopted to long-term acoustic emission-based structural health monitoring in [10]. Actually, signals in the time–frequency domain has better sparsity which has been demonstrated in the works [11,12]. CS-based sparse TFR of nonstationary signals in the presence of impulsive noise was carried out by simulations in [13]. Instantaneous frequency and time–frequency signature estimation was developed using CS in [14]. Nevertheless, the traditional orthogonal matching pursuit (OMP) was used in the reconstruction process in the above works [13] and [14]. A joint time–frequency distribution based on the Wigner–Ville distribution and CS is explored for radar signature analysis [15], which provided the localization of the Wigner–Ville with reduced cross terms. However, the compression performance was not mentioned in [15]. In addition, the traditional compression methods do the sampling and compression separately.

CS is utilized in recovering the sparsity TFR for the off-line and remote machine health monitoring in this work. The main contributions of the work are outlined as follows: (1) A novel parallel FISTA-like proximal decomposition algorithm (PFPDA) algorithm is proposed for reconstruction of sparse TFR from noisy observations; (2) a new framework for remote and off-line machine health condition monitoring is then introduced via the advancement in wireless communication; (3) The sparsity of the TFR for measured vibration signals have been verified which is the premise of CS-based method for the diagnosis applications. The remainder of the paper is organized as follows. In Section 2, CS theory is first briefly recalled. The proposed parallel FISTA-like proximal decomposition algorithm for sparse TFR is then given in Section 3. Simulation tests for the evaluation of the proposed method are presented in Section 4. The novel framework for remote machine health condition and practical applications for the proposed method in diagnosis of bearings and gears are conducted in Section 5. Conclusions are drawn in Section 6.

2. Compressive sensing theory

CS is a novel technique that enables sampling below Nyquist rate, without (or with little) sacrificing reconstruction quality. It is based on exploiting signal sparsity in some typical domains. For a piece of finite-length, real-valued 1-D discrete signal $\boldsymbol{s}$, its representation in the domain Ψ is

$$\mathbf{s} = \sum_{i=1}^{N} \psi_i x_i = \Psi \cdot \mathbf{x} \tag{1}$$

where $\mathbf{x} \in \mathbb{R}^N$ and $\mathbf{s} \in \mathbb{R}^N$ are $N \times 1$ column vectors, and $\Psi \in \mathbb{R}^{N \times N}$ is an $N \times N$ basis matrix with vectors $\{\psi_i\}$ $(i = 1, 2, \ldots, N)$ as a column. Signal $\mathbf{s}$ is K-sparse if K out on the coefficients of $\mathbf{x}$ are nonzero in the domain Ψ, and it is sparse if $K \ll N$. Take $M (K \leqslant M \leqslant N)$ linear, nonadaptive measurement of $\mathbf{s}$ through a linear transform Φ,

$$\mathbf{b} = \Phi \mathbf{s} = \Phi \Psi \mathbf{x} = A\mathbf{x} \tag{2}$$

where $\Phi \in \mathbb{R}^{M \times N}$ is an $M \times N$ matrix and each of its M rows can be considered as a basis vector, usually orthogonal and $\mathbf{b} \in \mathbb{R}^M$ is a column vector. Both $\mathbf{b}$ and $\mathbf{x}$ are formed by stacking the columns of their corresponding two-dimensional time–frequency plot. Signal $\mathbf{s}$ is thus transformed, or down sampled to an $M \times 1$ vector y. Given a vector $\mathbf{x}$, one may recover the desired underlying signal via an inverse transform, for example, an inverse DCT or wavelet transform depending on which basis is employed in sparse representation. The measurement matrix Φ must allow the reconstruction of the original signal from $M < N$ measurements.