



A novel strategy for signal denoising using reweighted SVD and its applications to weak fault feature enhancement of rotating machinery



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ABSTRACT

Singular value decomposition (SVD), as an effective signal denoising tool, has been attracting considerable attention in recent years. The basic idea behind SVD denoising is to preserve the singular components (SCs) with significant singular values. However, it is shown that the singular values mainly reflect the energy of decomposed SCs, therefore traditional SVD denoising approaches are essentially energy-based, which tend to highlight the high-energy regular components in the measured signal, while ignoring the weak feature caused by early fault. To overcome this issue, a reweighted singular value decomposition (RSVD) strategy is proposed for signal denoising and weak feature enhancement. In this work, a novel information index called periodic modulation intensity is introduced to quantify the diagnostic information in a mechanical signal. With this index, the decomposed SCs can be evaluated and sorted according to their information levels, rather than energy. Based on that, a truncated linear weighting function is proposed to control the contribution of each SC in the reconstruction of the denoised signal. In this way, some weak but informative SCs could be highlighted effectively. The advantages of RSVD over traditional approaches are demonstrated by both simulated signals and real vibration/acoustic data from a two-stage gearbox as well as train bearings. The results demonstrate that the proposed method can successfully extract the weak fault feature even in the presence of heavy noise and ambient interferences.

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1. Introduction

Rotating machinery, as one of the most critical classes of mechanical equipment, has been playing a vital role in modern industry. Due to the increasing use of rotating machines in harsh environment and remote distance, these machines are experiencing an accelerated degradation and inadequate maintenance actions due to limited accessibility. And also, the unexpected failures of these machines may lead to fatal breakdown, huge economic loss or even catastrophic casualties. Therefore, early warning of mechanical fault using advanced condition monitoring tools and health assessment methods has attracted considerable attention in both industry and academia [1,2].

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Vibration/acoustic analysis has been widely accepted as an effective tool for condition based maintenance (CBM) of rotating machinery [3]. However, with the progress of science and engineering, more and more rotating machines, such as gear systems of mine excavators [4–6] and helicopters [7,8], bearing systems of high speed trains [9,10] and wind turbines [11], have been working in harsh environments and continuously changing regimes. Consequently, their vibration/sound signals are manifested as non-stationary, complex modulation and heavy noise. These signal characteristics bring great challenges to signal analysis and interpretation. Therefore, extraction of the weak fault feature is a challenging issue in the community of CBM.

During the past decades, a variety of signal processing techniques have been developed for the signal denoising and feature extraction, including Wavelet transform(WT) [12,13], empirical mode decomposition (EMD) [14], spectral kurtosis [15], singular value decomposition (SVD), minimum entropy deconvolution [16–18], and stochastic resonance [19–21]. Among these methods, SVD has drawn increasing attention in recent years. Different from WT, SVD is a non-parametric signal analysis tool which can be implemented without pre-defined basis functions. Through correlation analysis, SVD is able to reveal the weak intrinsic pattern buried in a signal and suppress the noise with different distributions [22]. Moreover, SVD is considerably faster and easier to implement comparing with other signal processing techniques [23]. Owing to the above merits, SVD has been applied to a wide range of fields including fault detection, earthquake prediction, health monitoring of mechanical and civil structures, data compression and tensor decomposition.

In the field of CBM, Yang and Tse [24] investigated the optimal denoising order with the aid of singular entropy, and then developed an effective noise reduction method for vibration analysis based on SVD. Zhao and Ye [25] demonstrated the similarities between Hankel-SVD and wavelet transform. Based on their finding, the concept of singular value decomposition packet (SVDP) was further proposed and discussed in Ref. [26]. To select the effective singular values in SVD, difference spectrum was introduced to capture the abrupt change in the singular values which reflects the boundary between signal and noise [27]. Following this idea, a correlation coefficient based selection algorithm was presented by Qiao and Pan [28], to extract abrupt information which represents the weak fault feature of rolling bearings. In 2015, Liu et al. [29] utilized the singular values of Hankel-SVD as features for bearing fault diagnosis. Apart from the above time domain methods, a novel SVD-based denoising approach was recently proposed by Golafshan and Sanliturk [23], and it was shown that signal denoising can also be achieved in frequency domain.

In summary, the available SVD-based denoising methods are commonly based on finding an appropriate threshold to reconstruct a lower rank matrix for subsequent processing [23]. It is no doubt that this denoising scheme works well for signals measured from laboratory machines or test rigs. However, more and more diagnostic cases indicate that its performance is far from satisfactory when applied to signals collected from industrial fields, and this limitation has seriously affected the application of SVD in practice.

Different with the traditional SVD-based denoising methods, this study presents a novel criterion to select the most informative signal components by evaluating their periodic modulation intensity (PMI). It is shown that the proposed PMI has a clear physical meaning and is able to describe the vibration behavior of the rotating machines effectively. Based on the proposed information criterion, a novel reweighting strategy is then proposed to further enhance the weak but informative features in the vibration signal, and the proposed strategy is validated through both simulative and experimental studies. The advantages of the proposed method can be summarized as: (1) it is an adaptive denoising strategy and requires very few efforts for parameter selection and customization; (2) the proposed method reweights the signal components based on information content rather vibration energy, it is thus more effective than previous methods in highlighting weak but informative features. This makes the proposed method more suitable for incipient fault detection and diagnosis; and (3) the proposed information criterion, PMI, is closely related to the faulty behaviors of rotating machines.

The rest of this paper is organized as follows. The principle, implementation as well as limitation of SVD-based signal denoising technique are briefly reviewed in Section 2. In Section 3, the physical meaning and mathematical derivation of PMI are elaborated, and an RSVD based signal denoising technique is proposed. The effectiveness of the proposed method is validated by some simulations and experiments in Sections 4 and 5, respectively. Finally, conclusions are drawn in Section 6.

2. Principle and limitations of current SVD based signal denoising approach

2.1. A brief review of SVD based signal denoising approach

The singular value decomposition of an $m \times n$ real matrix \mathbf{A} can be formulated as a factorization of the following form

$$\mathbf{A} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T \quad (1)$$

where $\mathbf{U} = [u_1, u_2, \dots, u_m] \in \mathbf{R}^{m \times m}$, $\mathbf{V} = [v_1, v_2, \dots, v_n] \in \mathbf{R}^{n \times n}$ are orthogonal matrices. The column vectors of \mathbf{U} and \mathbf{V} are the orthonormal eigenvectors of $\mathbf{A}\mathbf{A}^T$ and $\mathbf{A}^T\mathbf{A}$, respectively; $\mathbf{\Sigma}$ is a diagonal matrix storing the singular values of \mathbf{A} in descending order, which is given by $\mathbf{\Sigma} = [\text{diag}(\sigma_1, \sigma_2, \dots, \sigma_l), \mathbf{0}] \in \mathbf{R}^{m \times n}$, where $l = \min(m, n)$ and $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_l$.

In Ref. [30], it is investigated that the original data matrix \mathbf{A} can be well approximated by a lower rank matrix using SVD. In signal processing, this property can be used for data reduction and it makes SVD a useful tool for de-noising of vibration signals. In general, signal denoising can be achieved by the following three steps.

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