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Sliding window denoising K-Singular Value Decomposition and its application on rolling bearing impact fault diagnosis

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ABSTRACT

The performance of sparse features extraction by commonly used K-Singular Value Decomposition (K-SVD) method depends largely on the signal segment selected in rolling bearing diagnosis, furthermore, the calculating speed is relatively slow and the dictionary becomes so redundant when the fault signal is relatively long. A new sliding window denoising K-SVD (SWD-KSVD) method is proposed, which uses only one small segment of time domain signal containing impacts to perform sliding window dictionary learning and select an optimal pattern with oscillating information of the rolling bearing fault according to a maximum variance principle. An inner product operation between the optimal pattern and the whole fault signal is performed to enhance the characteristic of the impacts' occurrence moments. Lastly, the signal is reconstructed at peak points of the inner product to realize the extraction of the rolling bearing fault features. Both simulation and experiments verify that the method could extract the fault features effectively.

1. Introduction

Rolling bearing is one of the most basic rotational mechanical components, which has been widely used in gearboxes, transmissions and reducers. When there are faults on rolling bearings, the safety performance of equipment will be affected, which might even lead to serious accidents [1]. Therefore, the diagnosis of the rolling bearing fault has been the emphasis of the industrial research. Theoretically, if there are faults (pitting, peeling and crack) on the surface of any part of the rolling bearing including outer ring, inner ring, rolling elements or cage, transient impacts will be generated between the defected surface and other contact surfaces [2]. However, thanks to environmental disturbances and other mechanical vibrations, the fault feature is submerged in noises, which is difficult to recognize [3].

Scholars have spared no effort to solve the problem and proposed many practical methods, such as empirical mode decomposition (EMD) [4], threshold denoising [5], wavelet transform [6] and sparse representation (SR). The core idea of sparse representation is to represent a signal by multiplying an over-redundant dictionary with its corresponding parameters, thus to get rid of the negative effect of noises. Because of its excellent performance on extracting features and suppressing noises, SR has been widely used in signal processing, computer vision, image recognition and mechanical faults diagnosis [7]. One of the most important step of SR is to decide the dictionary, which could be divided into static dictionary and learning dictionary [8]. The static dictionary is commonly obtained through transforming domain methods, such as over-redundant wavelet transform [9], super wavelet transform [10], curvelet transform [11] and contourlet transform [12], while the

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learning dictionary is more satisfactory to represent complex signals for its strong ability of self-satisfaction and feature description. The goal of the dictionary learning is to extract the real and effective feature information to the greatest extent. However, because of the noisy machine running environment and the unstable state, it is far from easy to learn the dictionary.

K-SVD is one of the most commonly used and effective dictionary learning method used in SR method [13]. Matching pursuit (MP) or Orthogonal Matching Pursuit (OMP) and Singular Value Decomposition (SVD) are performed in K-SVD to continuously update atoms in the dictionary. Based on the traditional K-SVD, Zhang proposed Discriminative-KSVD (D-KSVD) [14] by adding discriminative parameters to classify the image signal and utilizing more efficient OMP algorithm; Jiang put forward Label Consistent K-SVD (LC-K-SVD) [15], by adding classifying and label parameters to the target function. In the field of mechanical diagnosis, Yu applied K-SVD in rolling bearings early faults atom extraction, used the largest kurtosis as the stopping condition in the sparse coding step to promote the adaptivity [16]; Dong and Chen combined minimum entropy deconvolution (MED) and K-SVD method for incipient bearing fault detection [17], here the MED method is used to reduce the adverse effect of heavy background noise on K-SVD. Feng and Liang utilized the shift-invariant K-SVD (SI-KSVD) to extract the time shift invariant feature of planetary gearbox signals, which eliminates the signal segmentation process needed in K-SVD [18]; Yang and Chen proposed a data-driven method for bearing fault diagnosis based on shift-invariant K-SVD, which represents the impulses at different locations with the same characteristic by just one basis function through shift operation [19].

As shown in the above literature, although K-SVD has been proved to be effective in dictionary learning, there are two main drawbacks in the application, the first is that when the signal is relatively long, the dictionary will be too redundant to slow down the calculating speed, and the subjective parameter of K-SVD will be rather hard to be determined; the second is that if the noise is heavy, K-SVD will be apparently affected by the signal's phase and background noise, which will make it harder to extract the signal feature and affect the reconstruction precision consequently.

Inspired by the “pattern” idea of shift-invariant dictionary learning in Ref. [20], a new method called Sliding Window Denoising-KSVD (SWD-KSVD) is proposed for rolling bearing faults detection in this paper. In the method, considering the fact that all the periodic impacts caused by the local fault have a similar pattern, only a small signal segment is used in the K-SVD dictionary learning to get an optimal pattern containing the high-frequency oscillating characteristic of the fault impact. Then a sliding window inner product operation is performed between the optimal pattern and the overall signal. The occurrence moments of fault impacts are located by local peak points of the inner product. At last, bearing faults are detected effectively from the reconstructed signal at the local peak points selected.

The main contributions of the proposed method include: 1) Different from most previous literature in signal sparse representation, the K-SVD is not to get the learning dictionary for sparsely representing the whole signal, but for constructing only one pattern with the high-frequency oscillating characteristic of the impact fault, which is proved to be effective in extracting impact features. 2) The inner product operation between the optimal pattern and the overall signal can improve the signal to noise ratio and therefore highlight impact occurrence moments, improving the method's robustness to noises. 3) Only a small signal segment is needed in the pattern construction and a variance standard is proposed as a criteria to select the optimal pattern, which could accelerate the dictionary learning and eliminate the influence of signal phase.

The rest of the paper is structured as follows: In Section 2, the theory and procedure of the proposed SWD-KSVD are illustrated in detail. In Section 3, the effects of different SNR and starting point on the pattern are studied, and the effectiveness of the proposed method is proved by simulated results. The performance of the proposed method is also compared with those of other literature' methods in this section. In Section 4, the method is applied in the practical inner ring and outer ring impact fault detection. Conclusions are given in the last section.

2. Model of SWD-KSVD

2.1. Sparse representation theory

The principle of sparse representation is to represent the original signal with a dictionary and its coefficients [7]. Assume $\mathbf{D}\in R^{n\times m}$ is a dictionary, each column of it i.e. $\mathbf{d}_1,\ \mathbf{d}_2,\ \ldots,\ \mathbf{d_m}\in R^{n\times 1}$ is an atom, then the signal $\mathbf{s}\in R^{n\times 1}$ could be represented through $\mathbf{D}$ approximately

$$\mathbf{s}=\sum_{k=1}^{m}\mathbf{d}_k\alpha_k+\mathbf{r}=\mathbf{d}_1\alpha_1+\mathbf{d}_2\alpha_2+\cdots+\mathbf{d}_m\alpha_m+\mathbf{r} \tag{1}$$

where $\alpha_k\ \ (k=1,2,\ldots,m)$ are the sparse coefficients of the dictionary, $\mathbf{r}$ is the residual after the sparse representation which is expected to be as small as possible, i.e. $||\mathbf{r}||_2\leq\varepsilon$, where ε is a constant small enough. Eq. (1) can also be written as:

$$\mathbf{s}=\mathbf{D}\boldsymbol{\alpha}+\mathbf{r} \tag{2}$$

where $\boldsymbol{\alpha}=\{\alpha_1,\ \alpha_2,\ \ldots,\ \alpha_m\}^T$ is a coefficient vector.

The representation solution should be as sparse as possible and the reconstructed signal should be similar with the original $\mathbf{s}$ except for noises. Therefore, the optimal solution could be acquired by solving an l_0-norm optimization problem.